EFFECTS OF A PER-BAG TRASH COLLECTION FEE PROGRAM: EVIDENCE FROM A SYNTHETIC CONTROL METHOD

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ABSTRACT

Pay As You Throw (PAYT) policies are implemented worldwide to reduce waste. This paper estimates the effects of a PAYT policy in New Taipei City—per-bag trash collection fee (PBCF) program—on households' waste disposal. Under the PBCF, people have to buy certified bags for their unsorted waste, while sorted waste (food and recyclable waste) is disposed of for free. We apply a synthetic control method that allows cities/counties to have different trends in waste disposal. The estimation results using the city/county-level administrative data suggest that the PBCF decreases unsorted waste by about 27.2% and recyclable waste by about 20.8%. Food waste almost doubles in the short term, but the magnitude gradually reduces over time. Overall, the program reduces total waste by about 17.4%. These results suggest that waste avoidance behavior resulting from the PBCF appears not only in unsorted waste but also in recycling. Finally, we estimate that the welfare gain from the PBCF is about 30,000 NTD per household per year.

1 Introduction

Waste incineration, collection, and disposal leads to air and water pollution, which in turn negatively influence a city's appearance and human health. These negative externalities imply excess waste in the absence of government intervention. One way to internalize the externality of waste dumping is to adopt a Pay As You Throw (PAYT) or a unit-based pricing system.[1] It charges residents a fee for unsorted waste (garbage) and collects sorted waste (recycling and food waste) for free.[2] By determining disposal fees based on the quantity of unsorted waste, households have incentives to sort waste, recycle more, and reduce their overall waste generation. A PAYT policy can therefore increase social welfare by reducing the negative externality and costs for waste treatment (Fullerton and Kinnaman, 1996).[3] From a policy perspective, it is important to evaluate whether a PAYT policy is effective for waste reduction. Studying the effects of a PAYT policy on waste disposal also helps us better understand the mechanism of household responses to the policy.

This paper evaluates the effects of a PAYT policy in New Taipei City on households' waste disposal. The PAYT policy in New Taipei City is called the per-bag trash collection fee (PBCF), which was implemented in 2010. People have to buy certified bags to dump their unsorted waste—sorted waste are disposed of for free. We point out two effects of the PBCF on households' waste disposal behavior: waste avoidance and waste substitution. On one hand, households may prefer to buy lighter-weight goods and those using less packaging when they face a higher cost of dumping waste (waste avoidance effect). Waste avoidance by changes in purchasing choices can not only reduce households' garbage generation but also decrease recycling and food waste generation. On the other hand, households more carefully sort their waste and redirect more of it to recycling or food waste, which is free (waste substitution effect). The waste substitution effect changes the proportion of unsorted waste by correctly sorting recycling and food waste, while it leaves the amount of total waste intact.

Empirically, estimating the effects of the PBCF policy on waste disposal is a challenging

[1] According to Bueno and Valente (2019), PAYT systems are implemented worldwide, including in the United States (Fullerton and Kinnaman, 1996; Huang et al., 2011), South Korea (Kim et al., 2008), Japan (Usui and Takeuchi, 2014), the Netherlands (Linderhof et al., 2001; Allers and Hoeben, 2010), and Italy (Bueno and Valente, 2019).

[2] In this paper, waste dumping and waste disposal are used interchangeably. We also use unsorted waste and garbage interchangeably.

[3] There are other approaches to internalize negative externalities of waste dumping. See Fullerton and Kinnaman (1995) and Cheng et al. (2009) for discussion on various approaches to deal with excess waste, including unit pricing, disposal content fees, deposit-refund system, beverage container recycling policy, etc.

task because New Taipei City is different from cities not adopting it (all the other cities/counties except Taipei) in terms of not only their observed characteristics but also their unobserved determinants of waste disposal (e.g., residents' environmental consciousness). To address this challenge, researchers have applied the difference-in-differences or fixed effects estimation to control for time-invariant heterogeneity (Allers and Hoeben, 2010; Usui and Takeuchi, 2014). However, if the effects of unobserved determinants are not fixed over time, New Taipei City and those not adopting it may not share a parallel trend, causing biased difference-in-differences estimates for the effects of the PBCF on waste disposal. Indeed, as we show it later, the parallel trend assumption is not satisfied visually.

To address the non-parallel trend in waste disposal among cities/counties in Taiwan, we employ the synthetic control method proposed in Abadie and Gardeazabal (2003) and later expanded upon by Abadie et al. (2010).[4] The synthetic control method controls city-/county-specific trends by constructing a weighted average of control group (synthetic New Taipei City) such that the outcome trajectories of the synthetic control and New Taipei City in the pre-treatment period resemble each other. Since the synthetic New Taipei City is constructed using cities/counties without a PAYT system, we can use the outcome trajectories of synthetic New Taipei City as counterfactuals of New Taipei City. Therefore, the gap between outcomes of New Taipei City and synthetic New Taipei City in the post-treatment period can be attributed to the effects of the PBCF.

The credibility of a synthetic control estimator depends crucially on its ability to track the trajectory of the outcome variable for the treated unit before the intervention (Abadie et al., 2010; Abadie, 2020), and the synthetic New Taipei City we construct is able to closely track the outcomes of New Taipei City in the pre-intervention period. Our synthetic control estimates using city/county level administrative data from 2005 to 2016 yield four main findings. First, the synthetic control estimates suggest a significant and negative effect on households' garbage dumping (a 27.2% reduction). The volume of garbage being collected shows a remarkable and immediate decline when the policy is implemented, and the resulting level is maintained permanently. Second, we estimate a significant decline in recycling (20.8%). The effect on recycling is small and insignificant at the initial stage of the policy's implementation. However, the magnitude of this negative effect expands over time. This result indicates that waste avoidance dominates the substitution effect, and the habit of purchasing lighter-weight goods forms over

[4] See Abadie (2020) for an introduction and recent developments about synthetic control methods.

time.

Third, the PBCF policy has significantly increased food waste disposal (a 35.2% increase), suggesting the substitution effect is likely larger than the avoidance effect for this category of waste. We argue that this is due to the fact that food is a necessity, limiting the extent to which households can engage in waste avoidance. In addition, although the estimated effect increases remarkably when the policy was first implemented, it rapidly declines over time and become insignificantly different from zero three years after the policy was begun. One possible explanation is that the large amount of food waste dumping reminds households that they waste too much food, and their anti-waste consciousness induces them to change their food-buying behavior.

Fourth, the total waste significantly decreases, by 17.4%, in an immediate reaction to the new policy, and the effect persists over time. The reduction of total waste indicates that households are engaging in waste avoidance. Note that if there is only a substitution effect, it can only change the proportion of unsorted waste and sorted waste dumped by a household. However, if there is a decline in total waste, it implies that households are reducing the waste they generate and dump not only by sorting it but also reducing the actual amount of waste they produce.

Our paper makes three main contributions to the literature on evaluating the effects of a PAYT policy. First, this is the first paper that uses the synthetic control method to evaluate the household response to the PBCF policy in Taiwan and one of the first using this method to estimate the effects of a PAYT policy in the world.[5] Our studies are complementary to studies that apply other econometric methods to analyze the PBCF policy in Taiwan. Cheng (2019) applies a regression discontinuity design in time and uses district-level data from New Taipei City to find that unit pricing reduces unsorted waste by about 50%, increases food waste by 40%, and insignificantly increases recycling. Huang et al. (2019) use the difference-in-differences method and the city/county-level data from Taiwan, and they find that unsorted waste declined by 36%, food waste increased by 34%, and recycling waste increased by 7%. Compared to the difference-in-differences method, the synthetic control method allows the effects of unobserved heterogeneity to vary over time, and it provides a data-driven procedure for constructing a control group more comparable to New Taipei City. On the other hand, while the regression discontinuity in time can estimate effects near when the policy is implemented, the synthetic

[5] One exception is Bueno and Valente (2019), who study the effects of a PAYT policy in Trento, Italy on waste generation. Their synthetic control estimates suggest that the policy reduces unsorted waste by 37.5% and total waste by 8.6%, while it leads to an insignificant increase in recycling (6.1%).

control method can estimate a longer period of the policy effects.

Second, we find evidence that waste avoidance will not only emerge in unsorted waste but also in sorted waste. Most literature finds that per-unit pricing is effective to reduce unsorted waste, with mixed evidence for the effects on sorted waste (Fullerton and Kinnaman, 1996; Allers and Hoeben, 2010; Usui and Takeuchi, 2014; Bueno and Valente, 2019).[6] However, we find that unit pricing has a negative effect on the recycling rate in New Taipei City, which indicates that the waste substitution effect is dominated by the waste avoidance effect in New Taipei City.

Third, we find that the waste avoidance effect will be larger in the waste that results from non-necessary products. Although we show a negative effect on recycling, we observe a positive response in food waste dumping. Indeed, the PBCF's effect on each type of waste may depend on how necessary each category's contents are for households. For recycling, much of the content (glass, plastic, etc.) is not required for people's survival, but food is a necessity. Therefore, if the cost elasticity of recycling generation is larger than that of food waste, the waste avoidance effect of the PBCF will be larger for recycling but smaller for food waste.

The remainder of the paper is organized as follows. In Section 2, we describe the PBCF program of Taipei and New Taipei City. Section 3 discusses waste substitution, waste avoidance, and the expected effects of the PBCF on waste disposal. Section 4 explains the identification strategies of the difference-in-differences and synthetic control methods. In Section 5, we introduce the data and sample we use. Section 6 presents the empirical results. Section 7 display a welfare analysis for PAYT, and Section 8 concludes.

2 Background

To deal with the huge amount of garbage, the Taiwanese government spends a lot of money on waste collection and disposal. Therefore, the government collects a waste disposal fee from all residents. All cities/counties in Taiwan originally charged a water-based trash collection fee—under this system, each household is charged a garbage collection rate based on the amount of water they use. Specifically, the water-based collection fee is determined by the following

[6]Fullerton and Kinnaman (1996) find there is no significant effect on sorted waste, while Usui and Takeuchi (2014) find that such pricing increases the amount of sorted recycling. In particular, Allers and Hoeben (2010) emphasize that only a small proportion of decreases in unsorted garbage are due to households' improved recycling. See Huang et al. (2011) and Bueno and Valente (2019) for an excellent literature review on the effects of PAYT policies on waste generation.

formula:

$$\text{Fee (NTD)} = \text{Water consumption (liter)} \times \text{Collection rate in each city (NTD/liter)}$$

For instance, if a city's collection rate is NTD 3.7 per liter and a family consumes 100 liters in a month, the family will be charged NTD 370 for garbage collection.[7] Therefore, the formula above shows that the collection fee in the system is not related to the quantity of garbage a household generates—the marginal cost of waste dumping is zero. Instead, the more water a household uses, the more they have to pay for their waste dumping. People thus lack any incentives to reduce amount of garbage they generate or dump under a water-based system.

In 2000, Taipei started a novel PBCF Policy. The PBCF is a way to collect garbage fees based on the amount of garbage a household actually dumps. People have to buy certified bags at convenience stores to dispose their unsorted waste—sorted waste (food waste and recycling) are free to charge. Different types of bags are available, with prices ranging from 21 NTD for 20 packs of 3-liter bags to 273 NTD for 10 packs of 76-liter bags in 2020—0.36 NTD per liter. Under the PBCF, the more garbage a household produces, the more they have to pay for dumping it. Therefore, the PBCF offers incentives for households to correctly sort their waste and reduce the amount of garbage they dump.

In July 2008, the Shenkeng District, one of twenty-nine districts in New Taipei City, started a pilot PBCF policy. In May 2009, the Yingge, Bali, Shiding, Tucheng, and Yonghe districts joined the PBCF program. The remaining 23 districts gradually implemented the PBCF policy, in May, July, and November of 2010. The price per liter of bag was reduced from 0.42 NTD to 0.4 NTD in October 2012 and further reduced to 0.36 NTD in May 2019.[8] Note that a similar pilot policy was implemented in the Shigang District in Taichung City in 2000. However, the quantity of garbage in a single district will not have much of an effect on the city as a whole. Consequently, in the later analysis, we still view Taichung City as a control unit for New Taipei City.

[7] The collection rate in each city is available from the website of Taiwan Water Corporation: https://www9.water.gov.tw/service/03-2_Serv.aspx

[8] Detailed pricing about certified bags in New Taipei City can be found at https://crd-rubbish.epd.ntpc.gov.tw/disppagebox/ntpcepd/NtpCp.aspx?ddsPageID=BAGS&&dbid=5616176760.

3 Conceptual Framework

In this section, we discuss households' reaction to the user cost policy. We divide the household's behavior into two parts. One is waste generation, which involves the waste that households actually produce in each category (garbage, recycling, food waste, and bulky waste). The other is waste dumping, which is comprised of the waste of each type that households actually dispose of. For example, if a household uses up the content of a plastic bottle, but does not sort its trash and instead disposes of the plastic bottle with the garbage, then the bottle is produced as recycling but dumped as garbage.

Waste generation includes all of the waste that a household produces, including garbage, recycling, food waste, and bulky waste. The total waste is the sum of all these four categories. We consider if the cost of the waste generation increases, households will reduce their generation behavior by purchasing lighter-weight or less-packaging commodities. However, households may behave differently for different types of waste. For example, garbage (such as disposable chopsticks) or some recycling (such as extra plastic or paper packaging) can be easily avoided by the household. However, compared to garbage and recyclable waste, food waste has a lower cost elasticity because food is a human necessity, and households cannot easily change their purchasing behavior. Therefore, if the cost of recycling, including time, money, and effort, increases, then a household is likely to reduce their recycling generation because most recycling are not as necessary as food. If the cost of food waste generation increases, the amount of food waste that a household produces is unlikely to change due to the small cost elasticity.

In contrast, waste dumping refers to all the waste that a household disposes of, including unsorted garbage, recycling, food waste, and bulky waste. Similarly, the total waste is the summation of these four types. On the dumping side, we do not take illegal dumping into consideration; that is, all of the waste that a household produces is collected by either the government or private waste-disposal institutions. Second, since waste sorting takes time and effort, households are likely to throw non-garbage items into the garbage. Thus, garbage is considered unsorted waste. In this view, only a proportion of recycling and food waste generation is correctly disposed of, and the remainder is what is dumped as garbage (unsorted waste). Third, people can dump all garbage, recycling, and food waste into the garbage collection truck, but bulky waste that should be independently collected by the government or private cleaning companies is not allowed. This means that the access of bulky waste disposal is different from that of the other types of waste, so all the bulky waste is dumped correctly.

As demonstrated by above discussion, the amount of garbage dumping is composed of all garbage generation and some proportion of recycling and food waste generation. The PBCF policy in Taipei and New Taipei City charges a specific fee for unsorted waste on the garbage dumping side. Since the cost of garbage disposal increases as more garbage is dumped, households have an incentive to decrease the amount of garbage they are dumping. We discuss two ways for households to reduce their amount of garbage dumping—waste avoidance and waste substitution—and their implications.

One way is waste avoidance from the waste generation side: households reduce their overall waste production, which involves producing less garbage, less recycling, and less food waste, by purchasing lighter-weight goods or generating less non-essential waste. We might think that the waste avoidance only occurs in garbage; however, due to incorrect dumping, pricing on unsorted waste not only increases the cost of garbage disposal but also increases the cost of some proportion of recycling and food waste generation. Even if the household only intends to reduce the amount of garbage they are dumping, purchasing lighter-weight goods or those with less packaging may contribute to the reduction of recycling waste as well. Another possibility for waste avoidance is that producers produce fewer packaging goods due to changes in households' preferences regarding goods' packaging.[9] In addition, the waste avoidance effect is expected to be larger on recycling and smaller on food waste owing to the difference in their cost elasticities.

The second way is waste substitution from the waste dumping side: households reduce the amount of unsorted waste by sorting the trash they produce, that is, increasing the proportion of correct dumping. Note that waste substitution reduces unsorted waste and increases sorted waste, but leaves the amount of total waste unchanged. In contrast, waste avoidance reduces all types (total waste) of waste.

Although we cannot observe the amount of waste households generate, we can obtain data on households' waste dumping collected by the government. According to the household possible reactions mentioned above, after the PBCF policy is implemented, we predict that (1) the amount of garbage dumping will decrease due to increased costs; (2) the amount of recycling dumping could increase, decrease, or remain unchanged, depending on households' waste avoidance and waste substitution efforts; (3) because of the necessity property of food, which

[9] Fullerton and Wu (1998) mention that households' preferences for packaging or recyclable content of a product will influence upstream production of goods. In our paper, the unit pricing increase households' demand for lighter-weight goods, and it may induce firm providing lighter-weighted or less-packaging commodities.

limits the amount of waste avoidance that is possible, the amount of food waste dumping is likely to increase; (4) owing to its different method of disposal, the amount of bulky waste should not be affected by the policy; and (5) waste avoidance in terms of garbage, recycling, and food waste all contribute to the reduction of total waste.

4 Econometric Approach

To examine the predictions from previous section, we introduce the empirical model and its challenges to identify the effects of the PBCF on waste disposal. Then we discuss the synthetic control method for addressing these empirical challenges.

4.1 Empirical Model and Challenges to Identification

Consider the following econometric model to estimate the effects of the PBCF program on a household's waste disposal:

$$Y_{jt} = \delta_t + \beta D_{jt} + \lambda_t \mu_j + \epsilon_{jt}, \tag{1}$$

where Y_{jt} is the per capita per day garbage/recyclable/food/bulky/total waste in city/county j at time t, where t indicates an observation from year y and month m. D_{jt} is the treatment indicator, equal to one for New Taipei City since May 2010. Moreover, δ_t are time indicators, capturing trends in waste disposal common to all cities/counties in Taiwan. The error term has two components: $\lambda_t \mu_j$ and ϵ_{jt}. μ_j is a vector of unobserved city/county characteristics, and $\lambda_t \mu_j$ are city/county-specific trends in waste disposal driven by these unobserved characteristics. ϵ_{jt} are unobserved transitory shocks at the city/county level. β is the coefficient of interest: the effects of the PBCF on waste disposal.

The major challenge in identifying the effect of the PBCF (β) is that the city-/county-specific trends ($\lambda_t \mu_j$) are unobserved and possibly correlate with the indicator of the PBCF policy (D_{jt}). For example, residents in New Taipei City might be more environmentally conscious, causing a steeper trends in recycling rate than in cities/counties not adopting PBCF. If λ_t are constant—if each city/county shares the same trend in waste disposal—equation 1 becomes the conventional difference-in-differences or two-way fixed effects model:

$$Y_{jt} = \delta_t + \mu_j + \beta D_{jt} + \epsilon_{jt}. \tag{2}$$

Estimates of β are the difference-in-differences estimates, measuring the change in waste disposal in New Taipei City relative to that of the control cities/counties before and after 2010. β will identify the effects of the PBCF on waste disposal if the waste disposal in New Taipei City and that of the control group share the same trend in the absence of the PBCF policy. If this assumption does not hold, the difference-in-differences estimates will be biased for the causal effect of the PBCF policy on residents' waste disposal behavior. As we will see in Section 6, this parallel trend assumption may not be satisfied.

Our approach to address this challenge to identification is to use the synthetic control method introduced by Abadie and Gardeazabal (2003) and Abadie et al. (2010). It relaxes the parallel trends assumption and allows the effects of unobserved characteristics of aggregate units (cities/counties in this paper) to vary over time. The synthetic control method uses a data-driven procedure to construct a weighted average of all control cities/counties (the synthetic control) such that the outcomes of the synthetic control in the pre-treatment periods closely track that of the treatment group.[10] Intuitively, because the synthetic control is constructed from control cities/counties without the treatment, the outcome trajectories of the synthetic control can be used as the counterfactuals in the post-treatment period. We introduce the details of the synthetic control method in the next subsection.

4.2 Synthetic Control Method

We introduce the synthetic control method using a potential outcomes framework. For $j = 1, \cdots, J+1$ units, and time periods $t = 1, \cdots, T$, with T_0 is the number of pre-treatment periods, $1 \leqslant T_0 < T$. Suppose that $j = 1$ is the affected unit exposed to the event after T_0, and $j = 2, \cdots, J+1$ composes a group of comparison units—the donor pool. In our study, the affected unit is New Taipei City, and the donor pool represents all the cities in Taiwan except Taipei and New Taipei City. Suppose $Y_{jt}(0)$ is the potential outcome for city/county j at time t if it is not exposed to the intervention, and $Y_{jt}(1)$ is the potential outcome for city/county j at time t if it is exposed to the intervention. Note that we never observe both of the potential outcomes of Y_{jt}: $Y_{jt} = Y_{jt}(1)$ if the j-th unit is treated at time t and $Y_{jt} = Y_{jt}(0)$, otherwise.

[10]The synthetic control method can be viewed as a generalization of difference-in-differences design (Abadie et al., 2010; Abadie, 2020). It constructs a weighted average of control group such that the weighted average matches the treatment group's value of $\lambda_t \mu_j$ in each period. In contrast, each control unit receives the same weight in the difference-in-differences estimation (Doudchenko and Imbens, 2017).

Therefore, the observed outcome can be written as:

$$
\begin{aligned}
&Y_{jt} = Y_{jt}(0), \quad j = 2, \cdots, J+1; t = 1, \cdots, T, \\
&Y_{1t} = Y_{1t}(0), \quad t = 1, \cdots, T_0, \text{ and} \\
&Y_{1t} = Y_{1t}(1), \quad t = T_0 + 1, \cdots, T.
\end{aligned}
$$

The treatment effect on New Taipei City is $\alpha_{1t} = Y_{1t}(1) - Y_{1t}(0), \forall t > T_0$. The synthetic control method estimates the counterfactual outcome using a convex combination of the donor pool $\widehat{Y}_{1t}(0) = \sum_{j \neq 1} w_j Y_{jt}$, where w_j represents the weight for city/county j.[11] That is, the synthetic control estimator is $\hat{\alpha}_{1t} = Y_{1t}(1) - \sum_{j \neq 1} w_j Y_{jt}, \forall t > T_0$. According to Abadie et al. (2010) and Abadie (2020), if the pre-treatment outcomes and observable characteristics for New Taipei City and synthetic New Taipei City match well, then the bias of the synthetic control estimator will be small, as long as T_0 is large relative to the scale of transitory shocks.[12]

How do we estimate the weight for each control unit to construct the synthetic control? Suppose that X_j is a $(k \times 1)$ predictor vector composed of pre-treatment outcomes and observable features for each unit. Let $X_0 = [X_2, \cdots, X_{J+1}]$ be a $(k \times J)$ matrix that includes the predictors for all untreated units. Abadie et al. (2010) propose to choose a set of weights, $W = (w_2, \cdots, w_{J+1})'$, to minimize the distance between X_1 and $X_0 W$:

$$
\begin{aligned}
W^*(V) &= (w_2^*(V), \cdots, w_{J+1}^*(V))' \\
&= \underset{\substack{W \geqslant 0 \\ 1'W = 1}}{\text{argmin}} ||X_1 - X_0 W||_V \\
&= \underset{\substack{W \geqslant 0 \\ 1'W = 1}}{\text{argmin}} \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}
\end{aligned}
$$

In this equation, V is a $(k \times k)$ symmetric and positive semi-definite matrix. Abadie et al. (2010) choose a diagonal matrix $V = \text{diag}(v_1, \cdots, v_k)$ to minimize the pre-intervention mean square prediction error (MSPE) of the synthetic control estimator:

$$
V^* = \underset{V \geqslant 0}{\text{argmin}} \frac{1}{T_0} \sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{j \neq 1} w_j^*(V) Y_{jt} \right)^2 .
$$

[11] The convex combination represents that each control unit receives nonnegative weight ($w_j \geqslant 0$) and the sum of the weights equals 1 ($\sum_{j \neq 1} w_j = 1$). Doudchenko and Imbens (2017) relax these two restrictions.

[12] In addition, Abadie et al. (2010) also assume that the data generating process of $Y_{1t}(0)$ follows a linear factor model or an autoregressive model.

Therefore, using the above procedure, we can compute $W^*(V^*) = (w_2^*(V^*), \cdots, w_{J+1}^*(V^*))'$. Finally, the treatment effect can be computed as the difference between the observed and synthetic outcomes of New Taipei City:

$$\hat{\alpha}_{1,t>T_0} = Y_{1,t>T_0} - \sum_{j=2}^{J+1} w_j^*(V^*) Y_{j,t>T_0}. \tag{3}$$

Following Abadie et al. (2010), we make statistical inferences by conducting placebo tests. We pretend that each control city receives the treatment at the same period as New Taipei City and reassign the treatment to each city in the donor pool. Using a procedure described above, we can obtain a corresponding synthetic control estimate for city/county j: $\hat{\alpha}_{j,t}$. If the policy effect is truly different from zero, the magnitude of the treatment effect in New Taipei City should be unusually larger than that in the donor pool under a random permutation. In this case, the *p*-value can be computed as

$$\hat{p} = \frac{\sum_{j \neq 1} 1\left[\hat{\alpha}_j \geqslant \hat{\alpha}_1\right]}{J}.$$

While this method can provide a statistical inference for synthetic control estimates in each period after the treatment, the synthetic control estimates are convincing only when an assigned treatment group closely matches its corresponding synthetic control regarding their outcome trajectories in the pre-intervention period. Therefore, we drop the cities/counties that are poorly matched in the pre-intervention period when computing the *p*-value.

Alternatively, according to Abadie et al. (2010), we use a test statistic that measures the quality of the post-treatment fit relative to the quality of the pre-treatment fit. We calculate the ratio of the root mean square prediction error (RMSPE) between the post-treatment period and the pre-treatment period for each unit, and we compute the *p*-value based on the distribution of this ratio.[13] In contrast to the prior method, comparing RMSPE ratios does not require the elimination of the poorly-matched cities/counties because the ratio takes the quality of the pre-treatment fit into account. Nevertheless, this method does not provide inferences for the

[13] Specifically, the RMSPE ratio between the post- and pre-treatment periods is

$$\frac{\sqrt{\frac{\sum_{t=T_0+1}^{T}\left(Y_{jt}-\widehat{Y}_{jt}(0)\right)^2}{T-T_0}}}{\sqrt{\frac{\sum_{t=1}^{T_0}\left(Y_{jt}-\widehat{Y}_{jt}(0)\right)^2}{T_0}}},$$

where $\widehat{Y}_{jt}(0)$ is the outcome in period t of the synthetic control for unit j. See Abadie (2020) for details.

treatment effects over time, so we conduct statistical inferences using both methods.

5 Data and Sample

We construct a monthly panel data from January 2005 to May 2016 for 18 cities/counties in Taiwan: New Taipei City (enacted the PBCF in 2010) and a group of 17 comparison units—Changhua County, Chiayi City, Chiayi County, Hsinchu City, Hsinchu County, Hualien County, Kaohsiung City, Keelung City, Maioli County, Nantou County, Pingtung County, Taichung City, Tainan City, Taitung County, Taoyuan City, Yilan County, and Yunlin County. Note that we focus on the effects of the PBCF policy in New Taipei City. Taipei enacted the policy in 2000; therefore, Taipei is not a suitable comparison city for New Taipei City and is excluded from our sample.[14]

The outcome variables of interests are: the volume of (1) garbage (kg), (2) recycling (kg), (3) food waste (kg), (4) bulky waste (kg), and (5) total waste (kg). All these variables are all measured as per capita, per day. We calculate the outcome variables using the data from Taiwan's Environmental Protection Administration (EPA). The EPA's website provides a monthly balanced panel for waste from all cities/counties in Taiwan over the past two decades.[15] Table 1 shows the definition of each category of waste from the EPA.

Following Bueno and Valente (2019), the covariates are chosen to represent the socio-economic variables of each city, including (1) log average per capita disposable income, measured in NTD (*log(income)*), (2) average household size (*Size*), (3) educational attainment, measured as the share of the population with a college degree or higher (*College*), and (4) age structure divided into the share of the population with an age under 15 ($Age < 15$) and age over or equal to 65 ($Age \geq 65$).[16] We collect all these annual data from the National Statistics dataset from 2005 to 2016.[17]

The synthetic control method projects the pre-intervention outcomes and covariates of New Taipei City into the convex hull constructed by the variables of control cities/counties. If these variables of New Taipei City are far away from the convex hull, the control units cannot repro-

[14]Although not shown in the paper, our fixed-effects estimates are robust to include Taipei in the sample.

[15]The outcome data are available from https://erdb.epa.gov.tw/ERDBIndex.aspx.

[16]Other than these variables, Bueno and Valente (2019), also include Gini coefficients and tourism intensity as covariates.

[17]National Statistics: A dataset from Directorate-General of Budget, Accounting, and Statistics, Executive Yuan, R.O.C. (Taiwan). The covariates are available from https://statdb.dgbas.gov.tw/pxweb/Dialog/statfile9.asp.

duce the counterfactual outcomes of New Taipei City, leading to bias in the synthetic control estimation. Therefore, following Bueno and Valente (2019), we check the convex hull condition by presenting the boxplots of the pre-intervention outcomes and covariates for New Taipei City and control units in Figure 1.

For all variables except for the elderly percentage, the range of New Taipei city's pre-intervention outcome and covariates lie within the variables of control cities. We argue that this does not invalidate our empirical results for two reasons. On one hand, Botosaru and Ferman (2019) prove that as long as the outcome of interest matches well prior to the treatment, the bias of the synthetic control estimates will be bounded even if the covariates of a treated unit cannot be matched by a synthetic control. On the other hand, Abadie (2020) mentions that the fact that the value of a particular predictor for the treated unit cannot be closely approximated by the synthetic control may be less of a concern if the synthetic control closely tracks the trajectory of the outcome variable for the treated unit during the pre-treatment period. As we will see, the pre-treatment outcome of the synthetic controls closely matches the pre-treatment outcomes of New Taipei City. Therefore, the fact that the elderly percentage in New Taipei City is outside the range of that in the control cities may not bias the synthetic control estimates.

6 Results

As discussed in Section 4, the difference-in-differences estimates are unbiased if New Taipei City and the average of the control cities share the same trend in waste disposal. We examine this common trend assumption in Figure 2. As we can see, in general, the waste disposal in New Taipei City (solid line) and that in the control cities (dashed line) do not seem to have a comparable trend prior to 2010. Since the common trend assumption does not hold visually, we use the synthetic control method to construct a more reliable control group.

6.1 Synthetic Control Estimates

The synthetic control method relaxes the common trend assumption of the difference-in-differences approach and allows us to estimate the dynamic effects in a transparent way. The optimal weight $W^*(V^*)$ for the construction of synthetic New Taipei City is estimated via the procedure mentioned in Section 4. Table 2 reports the estimated weight. For garbage, the synthetic New Taipei City is constructed using Kaohsiung City, Taoyuan City, and a small proportion of Pingtung County and Taichung City, while all the other cities receive zero weight. In the pre-intervention periods, Chiayi City, Kaohsiung City, and Taichung City best reproduce New Taipei City with respect to recycling; Hsinchu City, Hsinchu County, Kaohsiung City, Miaoli County, and Taitung County with respect to food waste; Hsinchu City, Hualien County, Keelung City, and Taichung City with respect to bulky waste; and Kaohsiung City and Taichung City with respect to total waste.

We compare the predictors of New Taipei City and synthetic New Taipei City in Table 3. The predictors are average pre-treatment outcomes, outcomes in February 2008 and April 2006, and pre-treatment (2005-2009) city/county characteristics. Among these predictors, except the elderly population percentage, the values are almost identical between the real and the synthetic New Taipei City. By contrast, the simple average of all donors is less comparable to New Taipei City in terms of these predictors.

Figure 3 displays the waste trajectory of New Taipei City and its synthetic control. New Taipei City and its synthetic control exhibit similar trajectories in all five outcomes prior to the implementation of the PBCF, indicating that the synthetic control offers an appropriate comparison with New Taipei City. Therefore, we can use the outcomes of synthetic New Taipei City in the post-treatment periods as the counterfactual outcomes of New Taipei City and attribute the outcome differences between New Taipei City and its synthetic control to the effects of the PBCF.

After the main policy was begun (May 2010, first vertical dotted line), for garbage, the counterfactual of New Taipei City continuously decreases slowly over time. New Taipei City drops immediately between May and November 2010, and then decreases at a similar rate to its counterfactual.[18] It shows that the policy's effect on garbage disposal is immediate and persistent. Specifically, the average effect is a drop of 0.161 kg per capita per day, a 27.2% reduction compared to the pre-intervention mean.[19]

As for recycling, the counterfactual of New Taipei City continuously increases over time, but the outcome in New Taipei City hovers around the same level as when the policy was

[18]This time pattern is consistent with the fact that 23 districts in New Taipei City joined the PBCF program one after another between May and November of 2010.

[19]The synthetic control estimate for the policy's effect is

$$\frac{1}{T - T_0} \sum_{t>T_0} (Y_{1t} - \hat{Y}_{1t}^{\text{SC}}),$$

which is the average post-treatment effect for New Taipei City.

implemented. The average effect of the PBCF on recyclable waste is a reduction of 0.052 kg per capita, per day, a 20.8% decrease in the pre-intervention mean. The gap between the recyclable waste of New Taipei City and its synthetic control is larger later in the sample periods, suggesting that the effect of the PBCF program on recyclable waste is stronger in the long run.

The post-treatment differences in the amount of food waste in New Taipei City and the synthetic New Taipei City suggest that the effect of the PBCF on food waste is large and positive in the short run. Specifically, the magnitude of the effect reaches a peak in June 2011 (almost a 100% increase) but gradually decreases to zero over time. In addition, bulky waste shows a discernible increase later in the sample periods, but the magnitude of the increase appears to be small.

Finally, the time patterns of total waste are noisier, but these is a clear gap between New Taipei City and its synthetic control since 2010. The gap after the PBCF policy was begun is not surprising, because unsorted waste accounts for over half of total waste, and this policy leads to an immediate and persistent decrease in total waste. Specifically, the average effect of the PBCF on total waste in the post-treatment period is a decrease of 0.163 kg per capita, per day, a 17.4% reduction at the pre-intervention mean level.[20]

6.2 Statistical Inferences

For the statistical inferences of the synthetic control estimates, we conduct the placebo exercises shown in Figure 4. The thick lines represent the estimated treatment effects, which are the vertical differences between the treated and synthetic control lines in Figure 3. The thin lines are placebo-treatment effects—we iteratively assign treatment status to each of the 17 control cities/counties and estimate the placebo-treatment effects using the synthetic control method. As seen in the graphs of Figure 4, except for bulky waste, the placebo-treatment effects are generally smaller in magnitude than the actual treatment effects, suggesting the actual treatment effects are not driven by sampling variation.

We conduct a one-sided inference for our synthetic control estimates using the data shown in Figure 4. Specifically, we compute the p-values by dividing the number of estimated effects as large as the estimated effect for New Taipei City by the number of permutations. If the policy effect is larger (smaller) than zero, we should see that the actual treatment effect is unusually

[20] In Table B1 of the Online Appendix, we also present the difference-in-differences estimates (equation 2). However, as we have shown in Figure 2, the difference-in-differences estimates are likely to be biased because of the violation of its common trend assumption.

positive (negative) and large compared to the placebo-treatment effects, leading to a small p-value. Based on Abadie et al. (2010), we drop the donors that have a pre-RMSPE two times larger than the treated unit before calculating the p-values. Figure 5 shows that the estimated effects on garbage, recycling, food waste, and total waste for New Taipei City are extreme relative to placebo effects, implying small p-values.[21]

An alternative way to evaluate the significance of the estimates is to calculate the distribution of the RMSPE ratio (Abadie et al., 2010). The advantage of using the RMSPE ratio for statistical inference is that we do not need to discard ill-fitting placebo runs (Abadie et al., 2010)—these groups will have low RMSPE ratios because of their high pre-treatment RMSPE. Figure 6 displays the RMSPE ratio for all treated and donor cities. Consistent with Figure 5, only bulky waste is not significantly affected by the PBCF policy—p-values for garbage, recycling, food waste, and total waste are all 1/17, and the p-value for bulky waste is 13/17).

Based on our discussion in Section 3, there are two channels for the decrease in unsorted waste: waste avoidance and waste substitution. The fact that the recycling and the total waste decline substantially suggests that the waste avoidance effect plays an important role in the effects of the PBCF on waste dumping. In particular, the decrease in recycling dumping indicates that waste avoidance can also be reflected in sorted waste. On the other hand, the different responses in terms of recycling and food waste dumping for a household may be attributed to the cost elasticity of the waste. In addition, the remarkable decline in the effect of the PBCF on food waste dumping later in the sample periods may result from anti-waste consciousness regarding food. Due to the remarkable initial increases in food waste dumping since the PBCF began, households may find that they waste too much food and try to reduce their food waste production. Finally, consistent with our predictions in Section 3, the PBCF is estimated to have no effect on bulky waste dumping.

6.3 Robustness Check

We have discussed the main results from the synthetic control estimator. In this subsection, we conduct four exercises to examine the robustness of our synthetic control estimates.

Quality of Donors First, it seems possible that some residents of New Taipei City dump their wastes in nearby cities/counties to avoid the PBCF. Such spillover effects may reduce the validity of including these cities/counties in the donor pool. In addition, Shigang District

[21] p-values for garbage, recycling, food waste, bulky waste, and total waste are 1/17, 1/11, 1/6, 4/16, and 1/15.

in Taichung started the PBCF in 2000, causing concern that Taichung might not be a valid control unit. Therefore, as a robustness check, we drop the cities/counties near New Taipei City, including Keelung City, Taoyuan City and Yilan County, and Taichung City from the donor pool. Figure 7 suggests that the estimated counterfactuals based on the two donor pools have similar trajectories in both the pre- and post-treatment periods. The fact that our synthetic control estimates are robust to the exclusion of the cities/counties neighboring New Taipei City is consistent with the evidence from Huang et al. (2019) estimating that the spillover effects of the PBCF program are limited.

Pilot Policy Second, since the pilot policy started from July 2008 in some districts of New Taipei City, it might have some effects on waste disposal in these districts. If this is the case, using May 2010 as the cutoff for the treatment periods may be inappropriate. To address this concern, we move the beginning of treatment periods from May 2010 to July 2008 and estimate the PBCF's effects using the synthetic control method. As shown in Figure 8, we observe that the time pattern of synthetic New Taipei City using the alternative definition of the treatment cutoff resembles that obtained using the original definition. The robustness of backdating the intervention shows that the pilot policy in the pilot districts has limited influence on waste disposal at the city/county level.

Predictor Selection We also investigate how using different predictors for choosing synthetic control weights affects our results. In Figures B1 and B2, we generate synthetic controls without using covariates as predictors—we only use lagged outcome (February 2008, April 2006, and the pre-treatment means)—and present the corresponding RMSPE ratio tests. While the time patterns of the synthetic control without covariates are somewhat different from the time patterns of the synthetic control with covariates, as summarized in Table B2), the synthetic control estimates without covariates are qualitatively similar to the results including covariates as predictors.[22] More importantly, according to Abadie et al. (2010) and Abadie (2020), the credibility of a synthetic control estimator depends on its ability to track the trajectory of the outcome variable for the treated unit for an extended pre-intervention period. Given the fact that the synthetic control including covariates as predictors are more able to track the trajectory of waste disposals of the New Taipei City prior to 2010, we consider synthetic control estimates that include covariates as predictors as more convincing results.

[22] In addition, to control for households' recycling behavior formed before PAYT, we further include sorted waste (recycling and food waste) before PAYT as additional predictors other than socio-economic variables. As seen in Figure B3, the time patterns of the synthetic controls with or without sorted waste as predictors are markedly similar, and their synthetic control estimates are comparable to each other (Table B3).

Non-stationarity Finally, the waste outcomes clearly present non-stationary trends. Does the non-stationarity of outcome variables invalidate the synthetic control method? The synthetic control method proposed by Abadie et al. (2010) does not require data to be stationary. Rather, as Ferman and Pinto (2019) point out, the synthetic control method is very efficient in dealing with non-stationary trends. Ferman and Pinto (2019) show that the non-stationary common factor will not lead to bias in the synthetic control. However, the synthetic control is asymptotically biased if the treatment assignment is correlated with a stationary common factor. In order to figure out whether the synthetic control weights reconstruct the factor loadings associated with the stationary common factor, they recommend researchers should also assess the pre-treatment fit of the synthetic controls using de-trending data. Specifically, we follow their suggestion de-trending the waste series by subtracting the control's average in each period and apply their demeaned synthetic control estimator. As we can see from Figure 9, although the pre-treatment fit for de-trending data is not as good as the original case, the variation in the de-trended waste series is small relative to the post-treatment effect, suggesting the synthetic control bias due to the correlation between the treatment assignment and non-stationary common factor is limited.

7 Welfare Analysis

We have estimated the effects of the PBCF program using the synthetic control method. In this section, we investigate the cost and benefits of the PBCF program using the graphical framework in Fullerton and Kinnaman (1996) and Huang et al. (2019). Figure 10 displays the graphical analysis for the effect of the PBCF on social welfare. The households' private marginal benefit (MB) of waste dumping represents their demand for waste dumping. The social marginal cost (SMC) is composed of two major components—private marginal cost (PMC) and external marginal cost (EMC). The private marginal cost refers to the cost of producing pollutants, and the external marginal cost is the cost of diminishing environmental quality resulting from garbage abandonment and accumulation.

Without the PBCF program, households are not required to pay for garbage generation, so the PMC in this case is zero. As for the EMC, we use the estimate from Huang et al. (2019) that use the government garbage disposal cost as a proxy for the external marginal cost (US$ 6.16).[23] As we can see from Figure 10, without the PBCF, households maximize their utilities

[23] According to Huang et al. (2019), the garbage collection fee is US$ 0.05/kg, the administrative costs of waste

by dumping the amount of garbage at b, where MB=PMC. In this case, households' benefit is $\triangle Ofb$, and the social cost is $\square\, Ogcb$. On the other hand, to maximize social welfare, the optimal level of garbage dumping is at a, where the marginal benefit is equal to the social marginal cost. Comparing the situation without government intervention to the social optimum, we can see that the deadweight loss in the absence of PBCF is $\triangle\, abc$. The government can charge an optimal fee aj (US$ 6.16/kg) on households to attain the social optimum (Baumol and Oates, 1988; Boardman et al., 2011). The increasing private cost will lower waste generation to point a. Therefore, households' benefits decline ($\triangle\, agf$), and social costs decrease ($\square\, Ogaj$). The entire social cost can be compensated by the tax revenue ($\square\, Ogaj$).

To internalize the negative externality, the government can impose a collection fee on households' emissions (Fullerton and Kinnaman, 1995; Fullerton and Wu, 1998). As shown in the figure, if the New Taipei City government charges US$ 0.05/kg as a collection fee, households reduce their garbage production at e. Under PBCF, households' benefit is $\triangle\, hfe$, social cost is $\square\, Ogdi$, and the deadweight loss $\triangle\, ade$. Therefore, by comparing the deadweight loss between the post-treatment periods and the pre-treatment periods, the welfare gain due to the PBCF can be approximated by the area of trapezoid $\square\, bcde$. We summarize the above analysis in Table 4. According to our synthetic control estimates, the PBCF reduces garbage by 0.161 kg per capita, per day. We can calculate the average household reduction is 157.49 kg per household, per year (average household size from 2010–2016 is 2.68 people/household) As a result, the welfare gain (trapezoid $\square\, bcde$) is equal to US$ 952.95 (about 30,000 NTD) per household, per year.

8 Conclusion

We have applied the synthetic control method to study the effects of the PBCF policy in New Taipei City, a PAYT policy that charges unsorted waste through certified bags—food and recyclable waste are free of charge. We highlight the advantage of using the synthetic control method compared to the difference-in-differences (two-way fixed effects estimation)—it relaxes the common trend assumption of the difference-in-differences by constructing a weighted average of control group that closely tracks pre-treatment outcomes of the treatment group. We show that the common trend assumption does not visually hold in our study, while the synthetic

collection (EMC) is US$ 6.16/kg, where EMC includes administrating the waste collection fee (US$ 0.42/kg), operating expense for incineration plants (US$ 0.07/kg), and costs of managing landfills (US$ 5.66/kg).

New Taipei City reproduces the outcomes of New Taipei City reasonably well before the PBCF was implemented.

The outcome gaps between New Taipei City and synthetic New Taipei City in the post-treatment period suggest that the PBCF policy in New Taipei City is effective to reduce waste. The synthetic control estimates show households reduce unsorted waste, recyclable waste, and total waste by 27.2%, 20.8%, and 17.4%. The simultaneous and persistent decrease in these three types of waste suggest that the decline in unsorted waste is not only driven by the waste substitution effect but also the waste avoidance effect. In particular, the decline in recycling implies that the waste avoidance effect dominates the waste substitution effect in recycling behavior. On the other hand, food waste increases by 35.2% in the post-treatment period. Our interpretation for the increase in food waste is that food is more necessary than recyclable products, limiting the extent of waste avoidance for food.

There are two limitations of this paper. First, we assume no illegal dumping. Huang et al. (2019) use a difference-in-differences approach and find that the unit pricing in New Taipei City increases illegal dumping when the main policy is implemented but it drops steeply over time. If illegal dumping has a large impact on our estimates, we should observe a dramatic change in the amount of each kind of waste being dumped, but we do not. On the other hand, if illegal dumping is a serious problem, we might expect some districts to change or suspend the PBCF (Allers and Hoeben, 2010), but this did not happen. Our second limitation is that we cannot identify the amounts of waste avoidance and waste substitution precisely because we can only observe the waste dumping information collected by the government. The amount of waste dumping is affected by both households' waste avoidance and substitution behavior. Therefore, these two effects can be distinguished only when researchers or the government measure the amount of the recyclable items dumped as unsorted waste. In this way, more precise information on households' actual garbage and recycling generation from household can help us verify the amount of waste avoidance and substitution.

References

Abadie, A. (2010), “Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects,” *Journal of Economic Literature*, forthcoming.

Abadie, A., A. Diamond, and J. Hainmueller (2010), “Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California’s Tobacco Control Program,” *Journal of the American Statistical Association* 105(490), 493–505.

Abadie, A., A. Diamond, and J. Hainmueller (2015), “Comparative Politics and the Synthetic Control Method,” *American Journal of Political Science* 59(2), 495–510.

Abadie, A. and J. Gardeazabal (2003), “The Economic Costs of Conflict: A Case Study of the Basque Country,” *American Economic Review* 93(1), 113–132.

Allers, M. A. and C. Hoeben (2010), “Effects of Unit-based Garbage Pricing: a Difference-in-Differences Approach,” *American Economic Review* 93(1), 113–132.

Baumol, W. J. and W.E. Oates (1988), “The Theory of Environmental Policy (2nd ed.),” New York: *Cambridge University Press*.

Boardman, A. E., D. H. Greenberg, A. R. Vining, and D. L. Weimer (2011), “Cost-Benefit Analysis: Concepts and Practice (4th ed.),” *Pearson Education, Prentice Hall*.

Botosaru, I. and B. Ferman (2019), “On the Role of Covariates in the Synthetic Control Method,” *The Econometrics Journal* 22(2), 117–130.

Bueno, M. and M. Valente (2019), “The Effects of Pricing Waste Generation: a Synthetic Control Approach,” *Journal of Environmental Economics and Management* 96, 274–285.

Cheng H. W., D. Y. Chou, W. C. Yang (2009), “A Study On the Policy Effects of Extended Producer Responsibility: Beverage Container Recycling Policy in Taiwan,” *Academia Economic Papers* 37(4), 625–659.

Cheng Y. C. (2019), “The Effect of User-charge Policy on Household Waste Behavior,” Master Thesis, National Taiwan University.

Doudchenko, N. and G. W. Imbens (2017), “Balancing, Regression, Difference-in-differences and Synthetic Control Methods: A Synthesis,” *Working Paper*.

Ferman, B. and C. Pinto (2019), “Synthetic Controls with Imperfect Pre-treatment Fit,” *Working Paper*.

Fullerton, D. and T. C. Kinnaman (1995), "Garbage, Recycling, and Illicit Burning or Dumping," *Journal of Environmental Economics and Management* 29(1), 78–91.

Fullerton, D. and T. C. Kinnaman (1996), "Household Responses for Pricing Garbage by the Bag," *American Economic Review* 86(4), 971–984.

Fullerton, D. and W. Wu (1998), "Policies for Green Design," *Journal of Environmental Economics and Management* 36(2), 131–148.

Huang, J. C., J. M. Halstead, and S. B. Saunders (1998), "Managing Municipal Solid Waste with Unit-based Pricing: Policy Effects and Responsiveness to Pricing," *Land Economics* 87(4), 645–660.

Huang, Y. K., R. B. Stevens, and W. D. Shaw (2019), "Waste Reduction from Mandatory Recycling versus Unit-Based Pricing: Quasi-experimental Evidence from Taiwan.," *Working paper*.

Huang, J. C., J. M. Halstead, and S. B. Saunders (2008), "Unit Pricing of Municipal Solid Waste and Illegal Dumping: an Empirical Analysis of Korean Experience," *Environmental Economics and Policy Studies* 9(3), 167–176.

Linderhof, V., P. Kooreman, M. Allers, D. Wiersma (2001), "Weight-based Pricing in the Collection of Household Waste: the Oostzaan Case," *Resource and Energy Economics* 23(4), 359–371.

Usui, T and K. Takeuchi (2014), "Evaluating Unit-based Pricing of Residential Solid Waste: a Panel Data Analysis," *Environmental and Resource Economics* 58(2), 245–271.

9 Tables

Table 1: Categories of Waste in EPA's Data Set

Variables	Definition
Total waste (ton) (municipal waste)	Solid or liquid waste produced by households or other non-businesses
Garbage (ton) (unsorted garbage)	Municipal waste other than recycling, food waste and bulky waste
Recycling (ton) (recyclable waste)	Recyclable items such as plastic, food containers, etc
Food waste (ton)	Discarded raw and cooked food and its residues
Bulky waste (ton)	Large-scale municipal waste, such as furniture, bicycles, tree branches, etc.
Total waste per capita per day (kg) $= \frac{\text{total waste}}{(\text{days in each month})\times(\text{population in each city})}$	

Notes: The total waste in the EPA's data set is called municipal waste, which is subdivided into garbage, recyclable waste, food waste, and bulky waste.

Table 2: Synthetic New Taipei City: Estimated Weights

Control Units	Garbage	Recycling	Food	Bulky	Total
Changhua County	0.000	0.000	0.000	0.000	0.000
Chiayi City	0.000	0.307	0.000	0.000	0.000
Chiayi County	0.000	0.000	0.000	0.000	0.000
Hsinchu City	0.000	0.050	0.041	0.184	0.000
Hsinchu County	0.000	0.000	0.132	0.000	0.000
Hualien County	0.000	0.000	0.000	0.238	0.000
Kaohsiung City	0.707	0.117	0.588	0.000	0.651
Keelung City	0.000	0.000	0.000	0.567	0.000
Miaoli County	0.000	0.000	0.001	0.000	0.000
Nantou County	0.000	0.000	0.000	0.000	0.000
Pingtung County	0.071	0.000	0.000	0.000	0.000
Taichung City	0.053	0.525	0.000	0.011	0.349
Tainan City	0.000	0.000	0.000	0.000	0.000
Taipei City	-	-	-	-	-
Taitung County	0.000	0.000	0.237	0.000	0.000
Taoyuan City	0.168	0.000	0.000	0.000	0.000
Yilan County	0.000	0.000	0.000	0.000	0.000
Yunlin County	0.000	0.000	0.000	0.000	0.000

Notes: This table shows the estimated weights for comparison units. Each donor receives a weight that minimizes the objective function of the synthetic control method to compose a synthetic New Taipei City.

Table 3: Predictor Balance

	Garbage			Recycling			Food		
	Treated	Synthetic	Sample	Treated	Synthetic	Sample	Treated	Synthetic	Sample
Mean (kg)	0.592	0.587	0.566	0.250	0.256	0.259	0.062	0.064	0.078
Feb.2008 (kg)	0.635	0.592	0.577	0.283	0.276	0.284	0.065	0.072	0.094
April.2006 (kg)	0.561	0.583	0.580	0.182	0.196	0.229	0.065	0.060	0.073
log(income) (NTD)	12.515	12.468	12.416	12.515	12.419	12.416	12.515	12.439	12.416
Age<15 (%)	17.036	17.348	17.738	17.036	19.040	17.738	17.036	17.378	17.738
Age$\geq$ 65(%)	7.544	9.357	11.446	7.544	9.081	11.446	7.544	10.455	11.446
College (%)	33.250	31.565	29.284	33.250	37.294	29.284	33.250	28.505	29.284
Household Size (persons)	2.896	2.930	3.140	2.896	3.102	3.140	2.896	2.946	3.140

	Bulky			Total		
	Treated	Synthetic	Sample	Treated	Synthetic	Sample
Mean (kg)	0.032	0.032	0.021	0.937	0.936	0.923
Feb.2008 (kg)	0.030	0.034	0.022	1.013	1.002	0.977
April.2006 (kg)	0.048	0.040	0.018	0.856	0.893	0.900
log(income) (NTD)	12.515	12.479	12.416	12.515	12.463	12.416
Age<15 (%)	17.036	17.375	17.738	17.036	17.550	17.738
Age$\geq$ 65(%)	7.544	10.614	11.446	7.544	9.064	11.446
College (%)	33.250	30.576	29.284	33.250	33.146	29.284
Household Size (persons)	2.896	2.847	3.140	2.896	2.970	3.140

Notes: Predictors are shown in the first column with the pre-treatment mean of outcome, outcome in February 2008, outcome in April 2006 and some pre-treatment (2005-2009) co-variates. We report the value of treated unit, synthetic control, and the mean of the donor pool for each of the subcategories of waste and total waste.

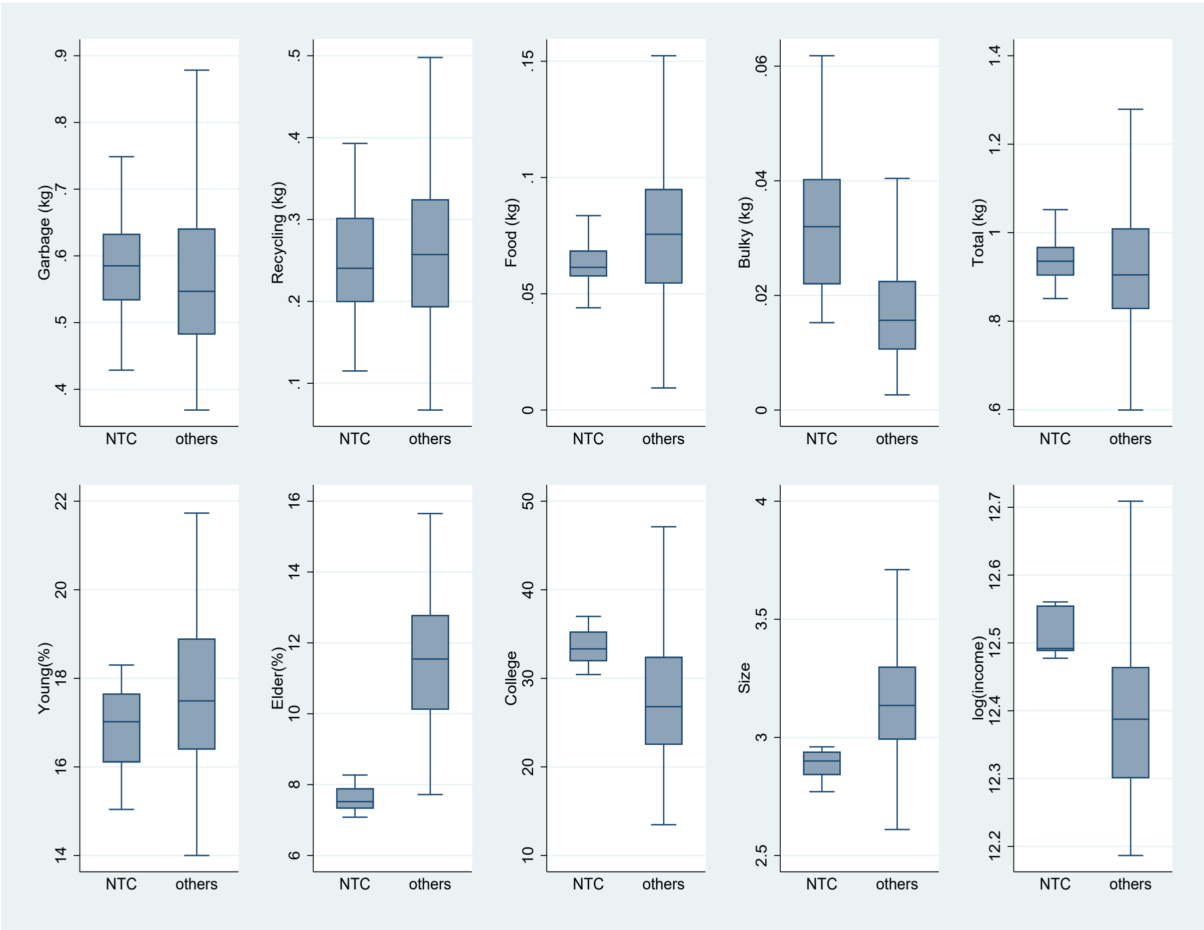
Table 4: Cost-Benefit Analysis

	Collection Fee	Polluter's Benefit	Social Cost	Collection Revenue	Deadweight Loss
Before	–	△Ofb	☐Ogcb	–	△abc
Optimal	aj	△agf	☐Ogaj	☐Ogaj	–
After	ei	△hfe	☐Ogdi	☐Ohei	△ade
Change					☐bcde

Notes: This table display the cost-benefit analysis corresponding to Figure 10. We list the collection fee, households' benefit, social cost, government collection revenue and deadweight loss in pre-treatment, post-treatment and the social optimal case. The welfare gain due to policy change can be calculated as the change in deadweight loss.

10 Figures

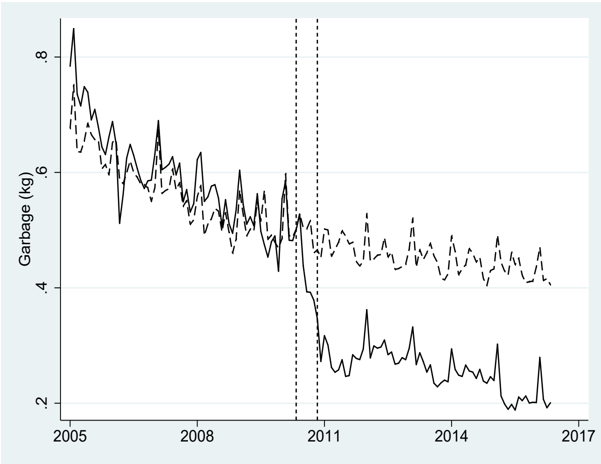
Figure 1: Descriptive Statistics



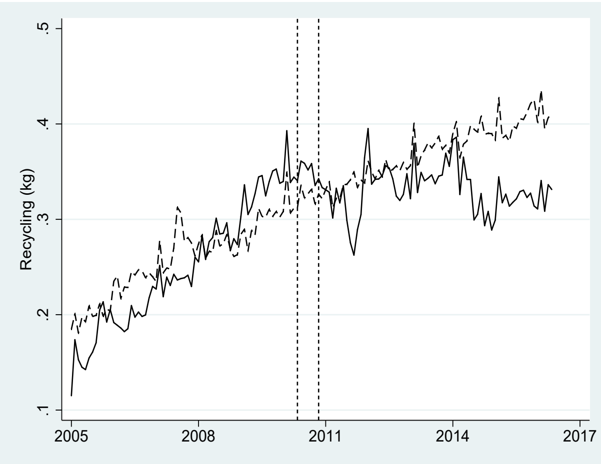
Notes: The figure above shows the boxplots of the pre-treatment characteristics of New Taipei City and donors. The boxplots record the upper adjacent value, 75th percentile, median, 25th percentile and lower adjacent value of these variables.

Figure 2: Waste Disposal for New Taipei City and Control Cities

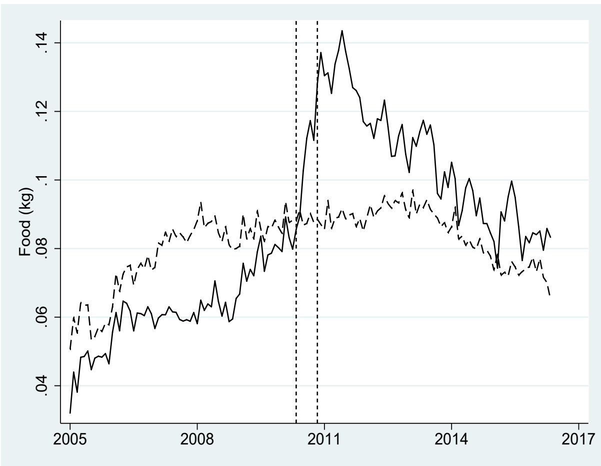
(a) Garbage



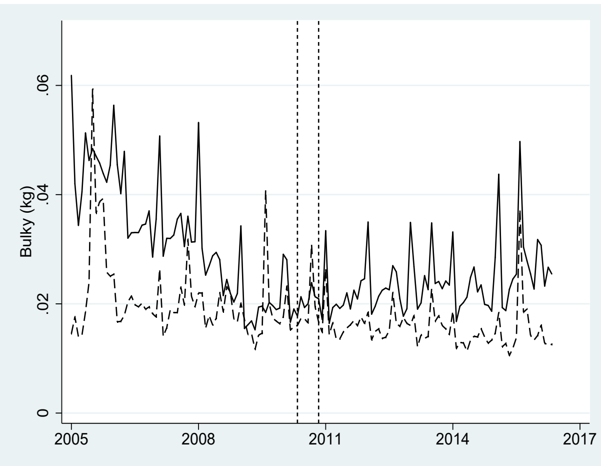
(b) Recycling



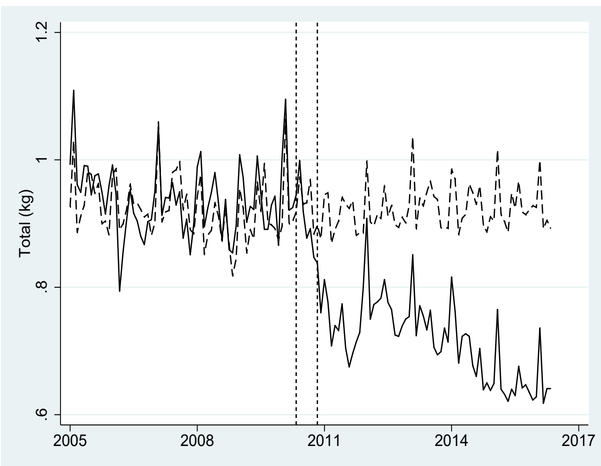
(c) Food



(d) Bulky



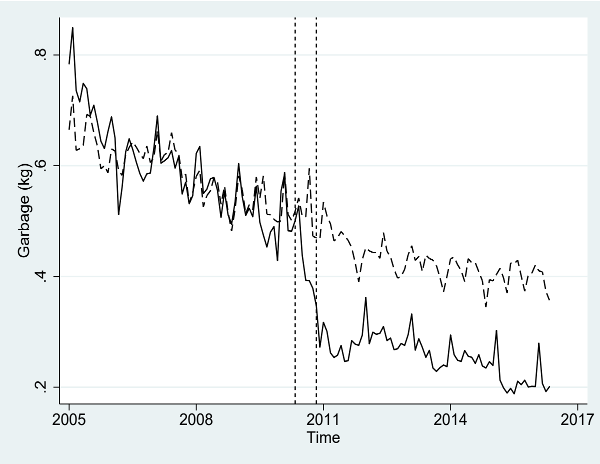
(e) Total



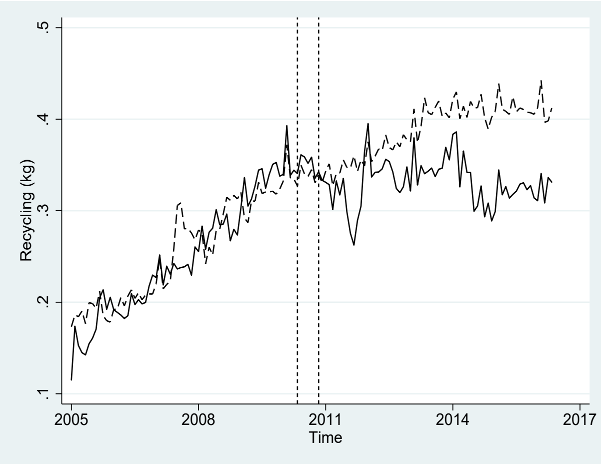
Notes: This figure shows the average waste dumping per capita per day (kg) each month from January 2005 to May 2016 for New Taipei City (solid) and the control cities (dashed). The two vertical lines denote May and November of 2010, when the main PBCF policy was implemented in 23 districts of New Taipei City.

Figure 3: Waste Disposal for New Taipei City and Synthetic New Taipei City

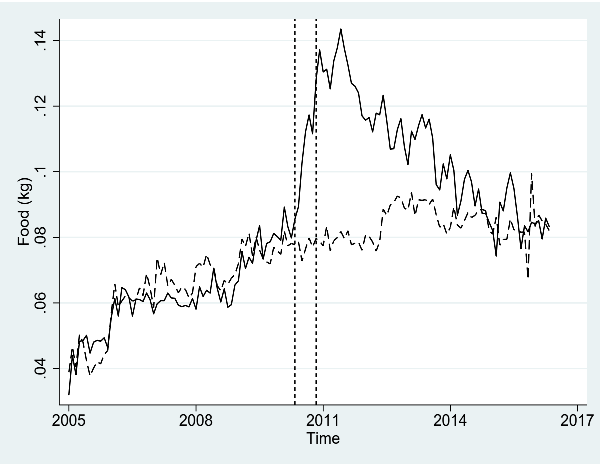
(a) Garbage



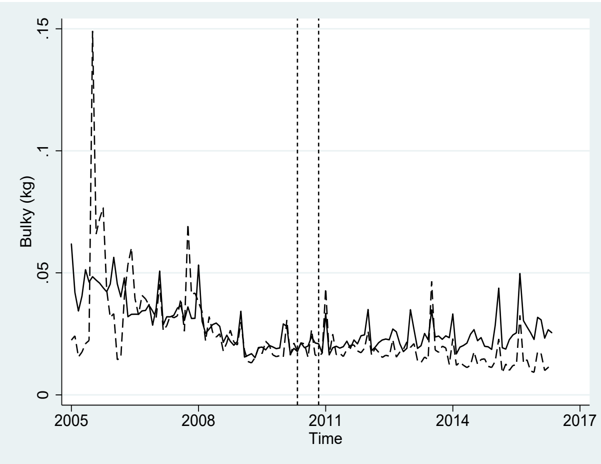
(b) Recycling



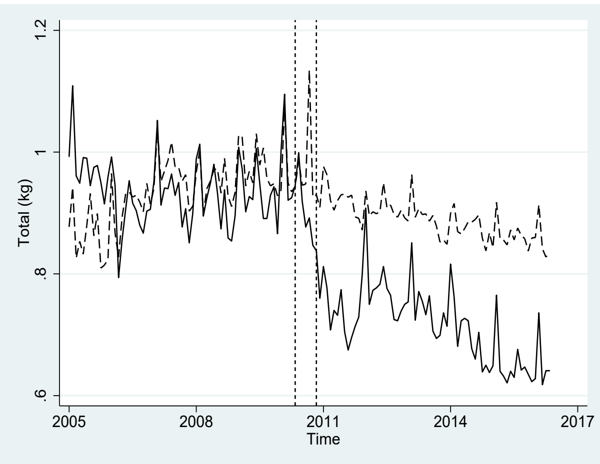
(c) Food



(d) Bulky



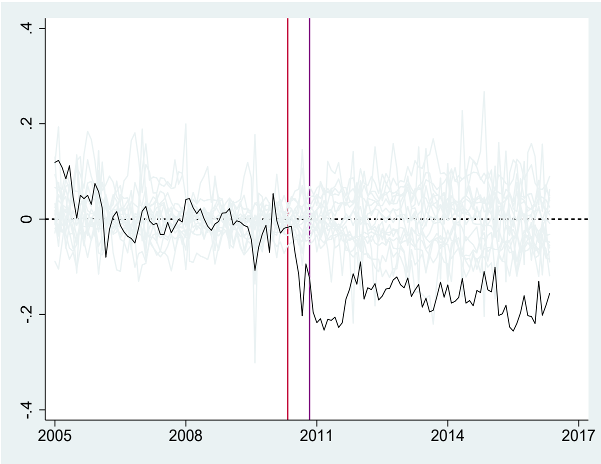
(e) Total



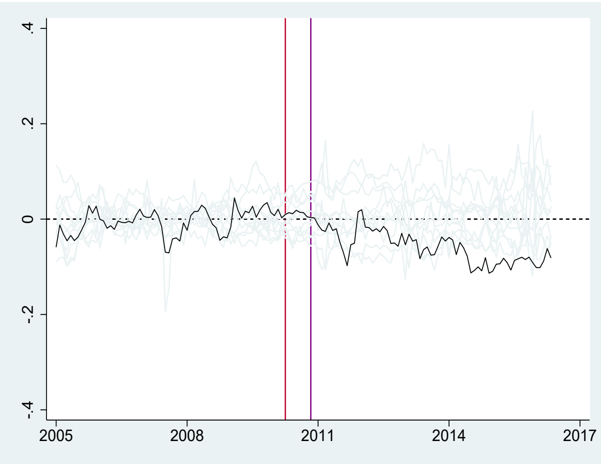
Notes: This figure shows the average waste dumping per capita per day (kg) each month from January 2005 to May 2016 for New Taipei City (solid) and the control cities (dashed). The two vertical lines denote May and November of 2010, when the main PBCF policy was implemented in 23 districts of New Taipei City.

Figure 4: Per-capita Per Day Waste Disposal Gaps in New Taipei City and Placebo Gaps in 17 control Cities/Counties

(a) Garbage

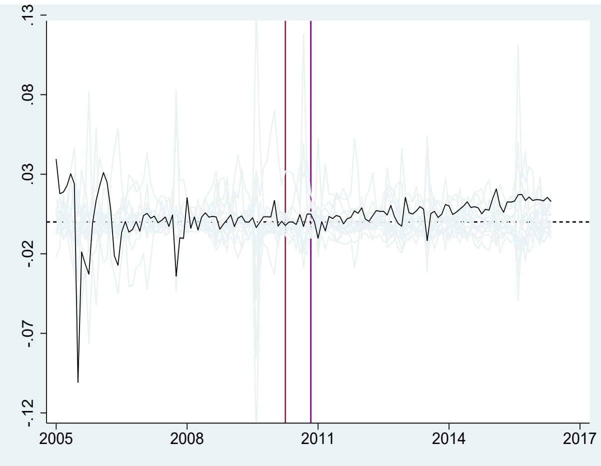


(b) Recycling



(c) Food

(d) Bulky

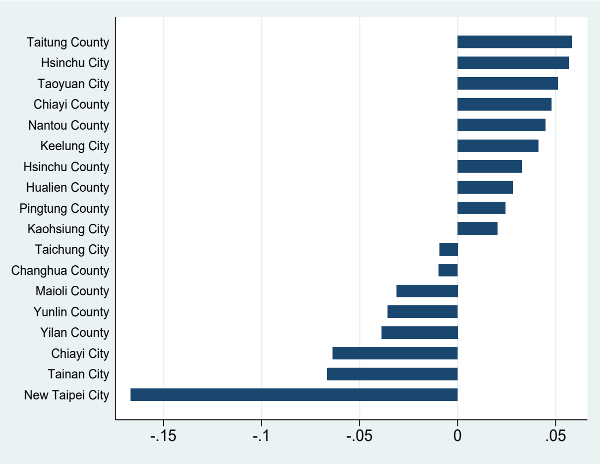


(e) Total

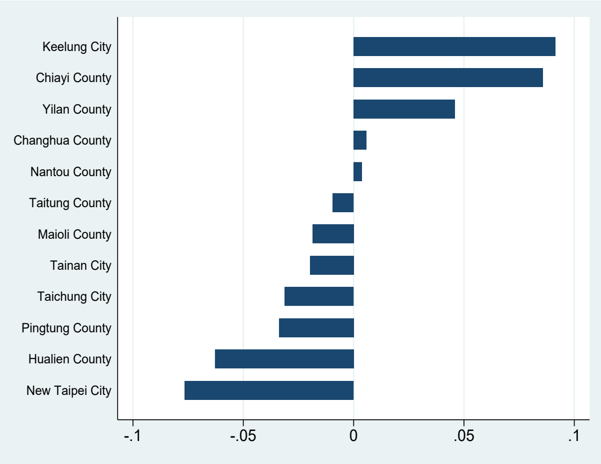
Notes: Per day per capita waste gaps in New Taipei City and placebo gaps in 17 control cities/counties (discards cities/counties with pre-treatment RMSPE two times higher than New Taipei City's). The two vertical lines denote May and November of 2010, when the main PBCF policy was implemented in 23 districts of New Taipei City.

Figure 5: Average Post-treatment Effects

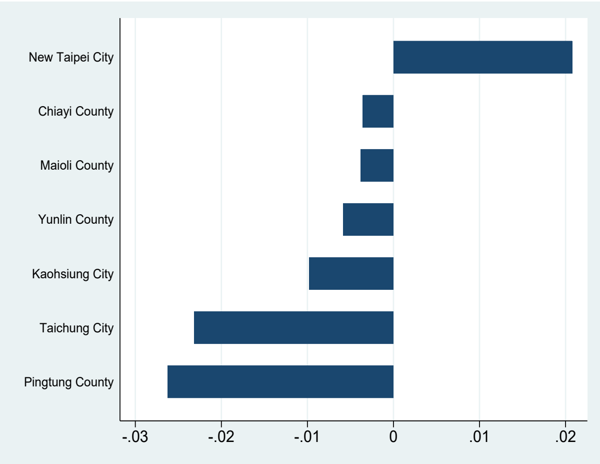
(a) Garbage



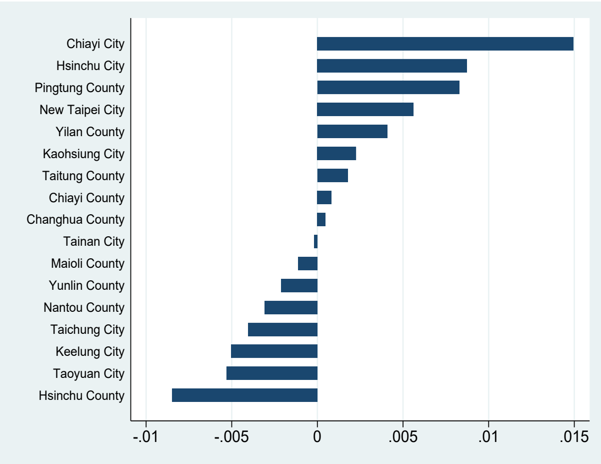
(b) Recycling



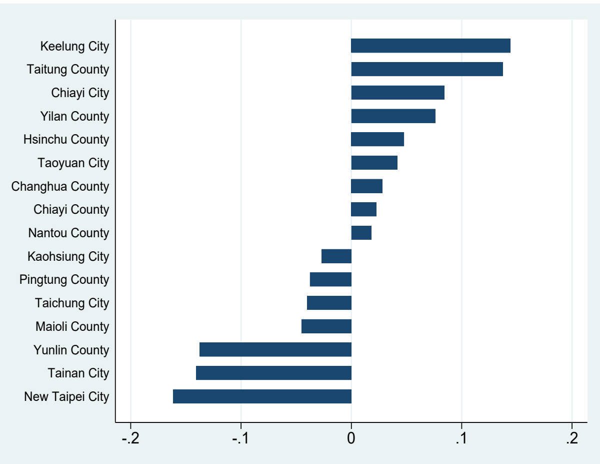
(c) Food



(d) Bulky



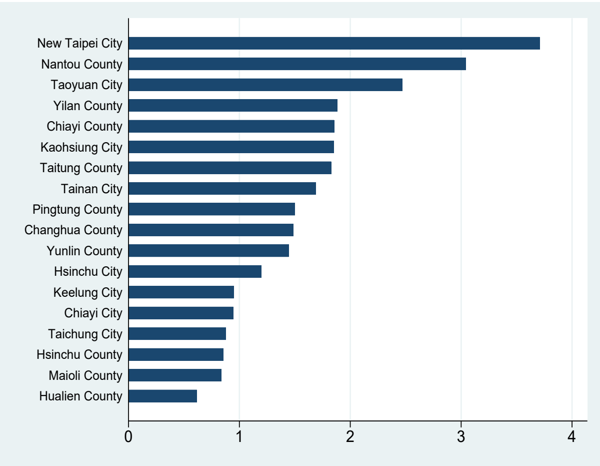
(e) Total



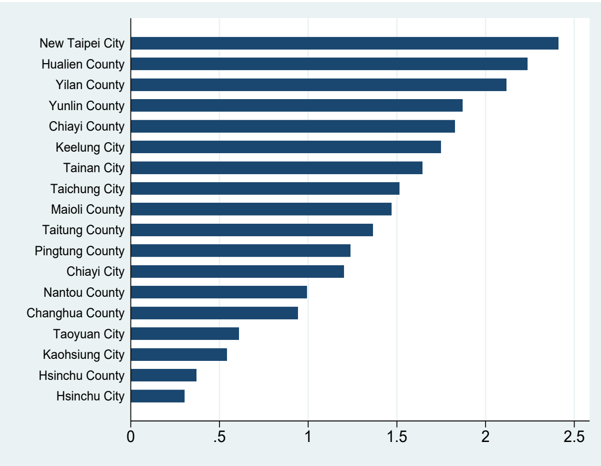
Notes: These graphs shows the average post-treatment effects in each city. We discard cities/counties with pre-treatment RMSPE two times higher than New Taipei City's.

Figure 6: RMSPE Ratios

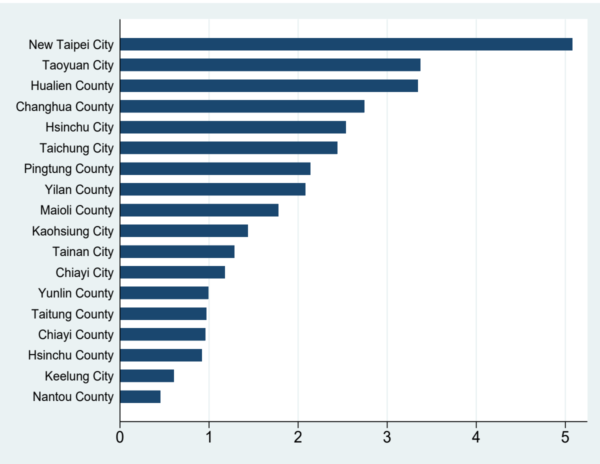
(a) Garbage



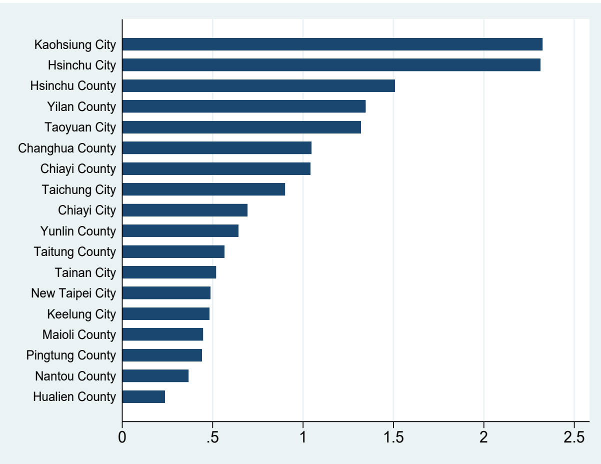
(b) Recycling



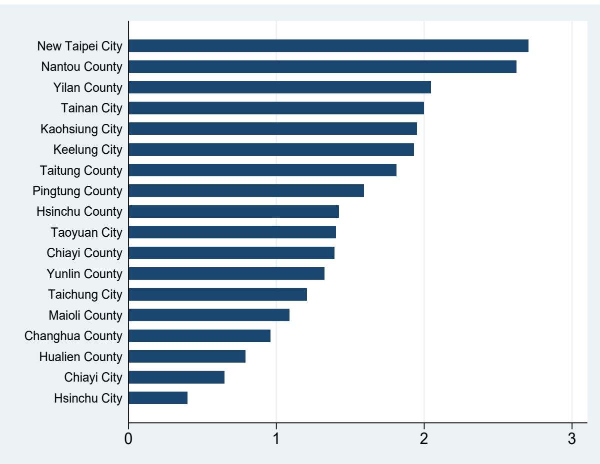
(c) Food



(d) Bulky



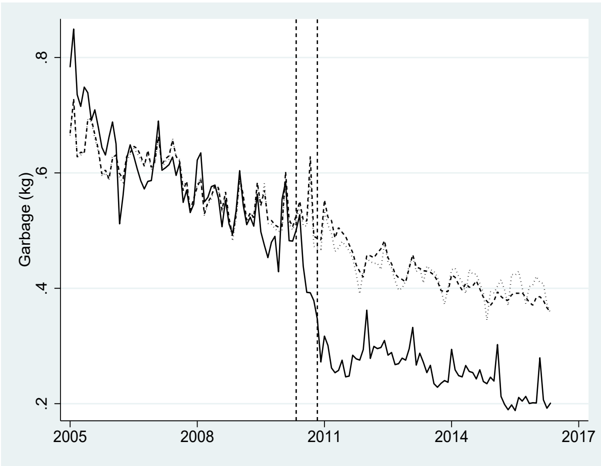
(e) Total



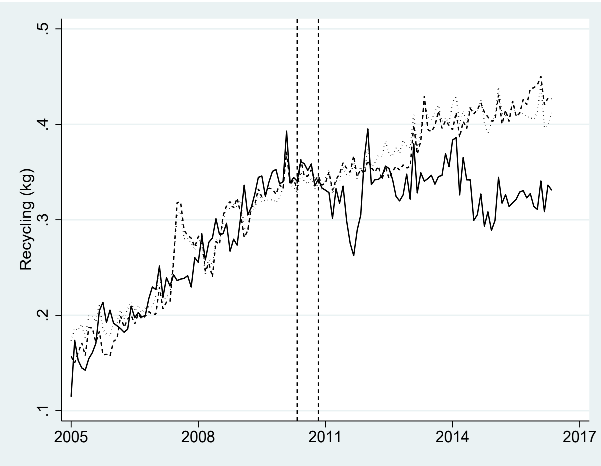
Notes: This figure displays the ratio of post-RMSPE and pre-RMSPE for New Taipei City and the 17 donors.

Figure 7: Robustness: Exclude Neighboring Cities/Counties

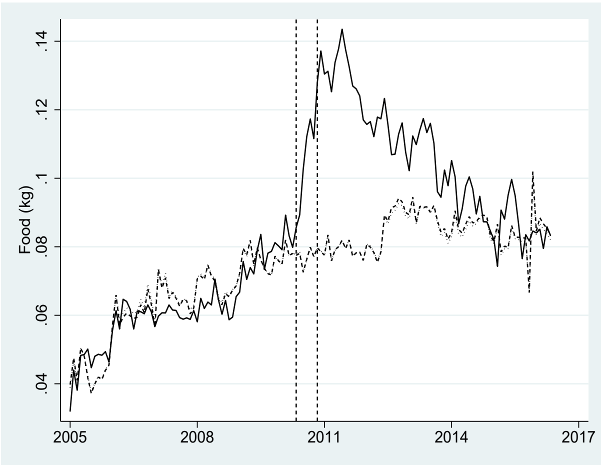
(a) Garbage



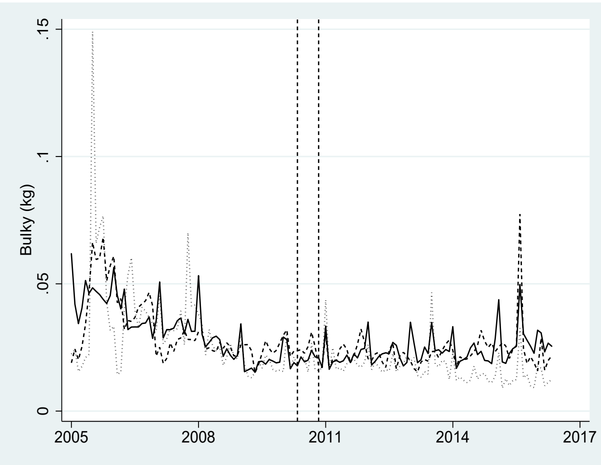
(b) Recycling



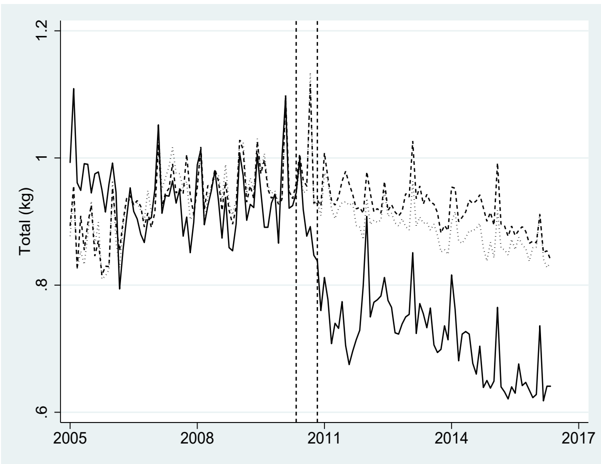
(c) Food



(d) Bulky



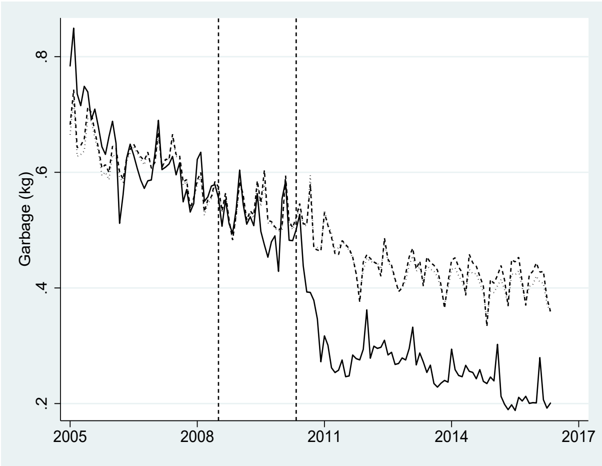
(e) Total



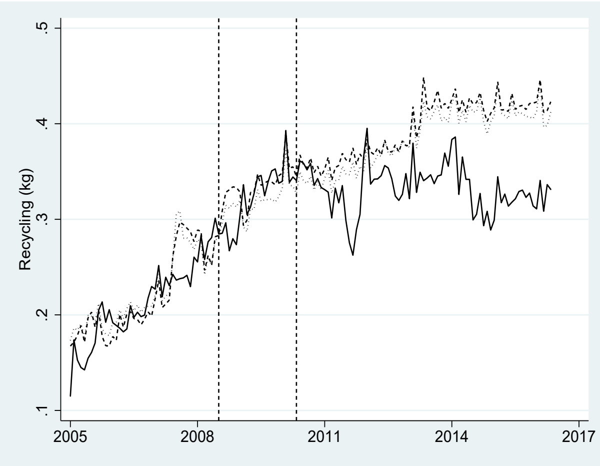
Notes: This figure shows the robustness when the donors that might be influenced by spillover effects (Keelung City, Taoyuan City and Yilan County) were discarded, as well as Taichung City where Shigang District implemented a pilot unit-pricing policy. The solid line denotes New Taipei City. The dotted line denotes synthetic New Taipei City generated by the original donor pool and the dashed line is generated by the donor pool excluding neighboring cities/counties and Taichung City.

Figure 8: Robustness: Backdating to Consider Pilot Policies

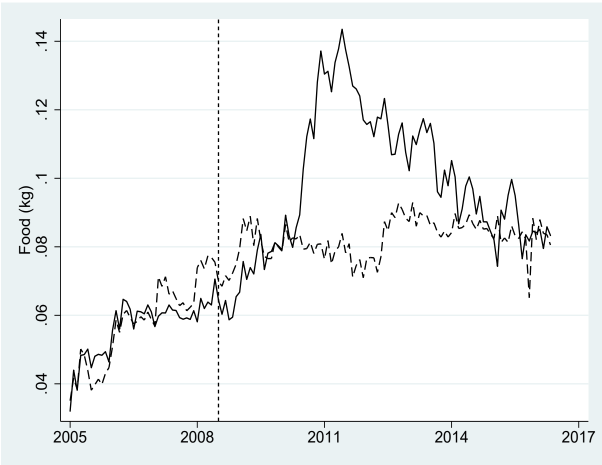
(a) Garbage



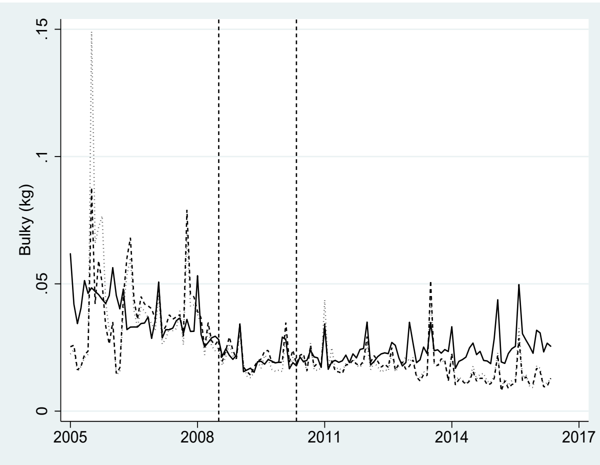
(b) Recycling



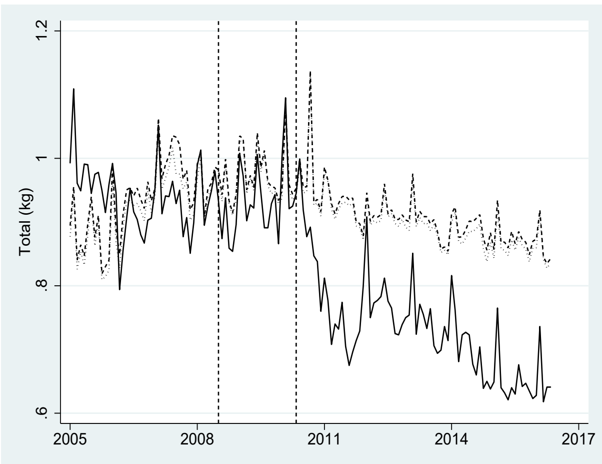
(c) Food



(d) Bulky



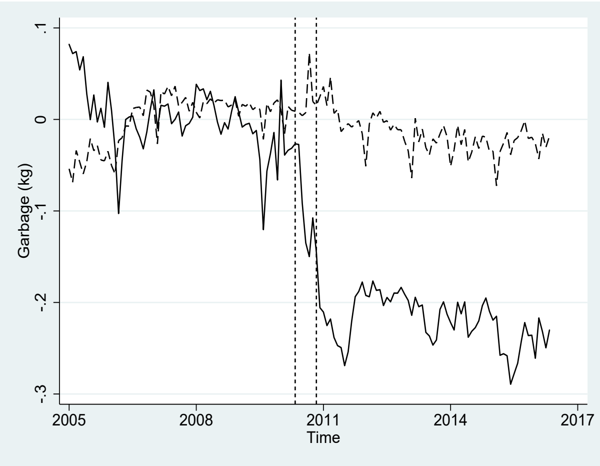
(e) Total



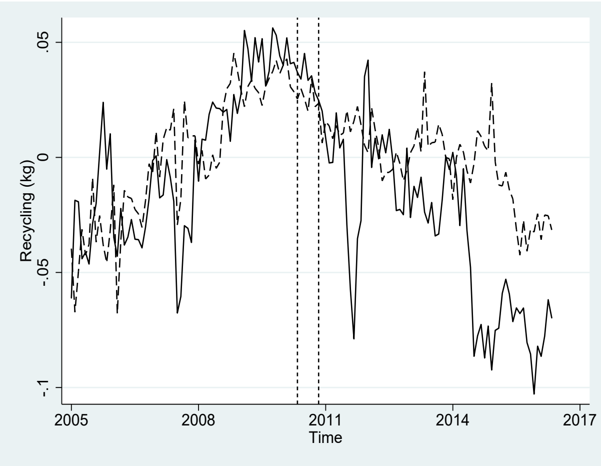
Notes: These graphs shows the robustness of backdating the post-treatment period in consideration of the pilot policy that was implemented beginning in July 2008. The first dashed line denotes July 2008, and the second denotes May 2010. The solid line denotes New Taipei City. The dotted line constructs a synthetic New Taipei City using periods before May 2010 as the pre-treatment period. The dashed line uses periods before July 2008 as the pre-treatment period.

Figure 9: Synthetic Controls Using De-Trended Data

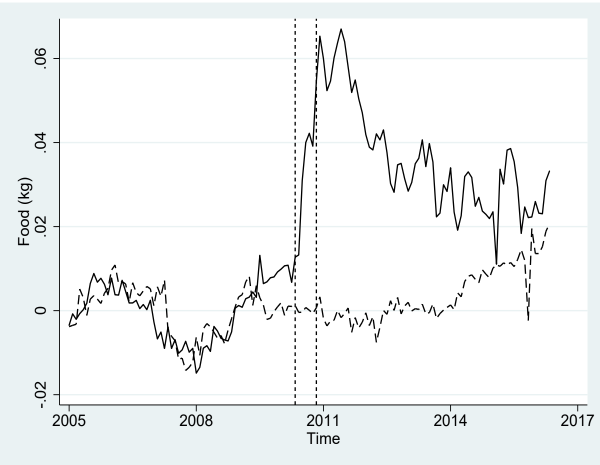
(a) Garbage



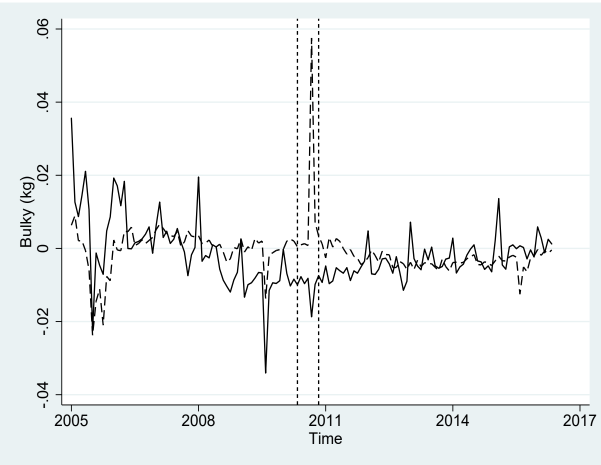
(b) Recycling



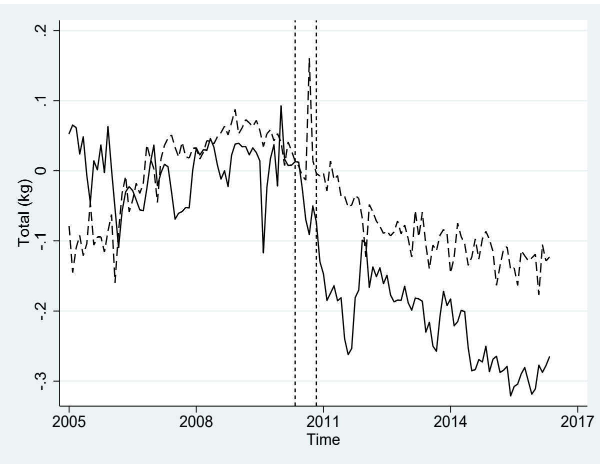
(c) Food



(d) Bulky

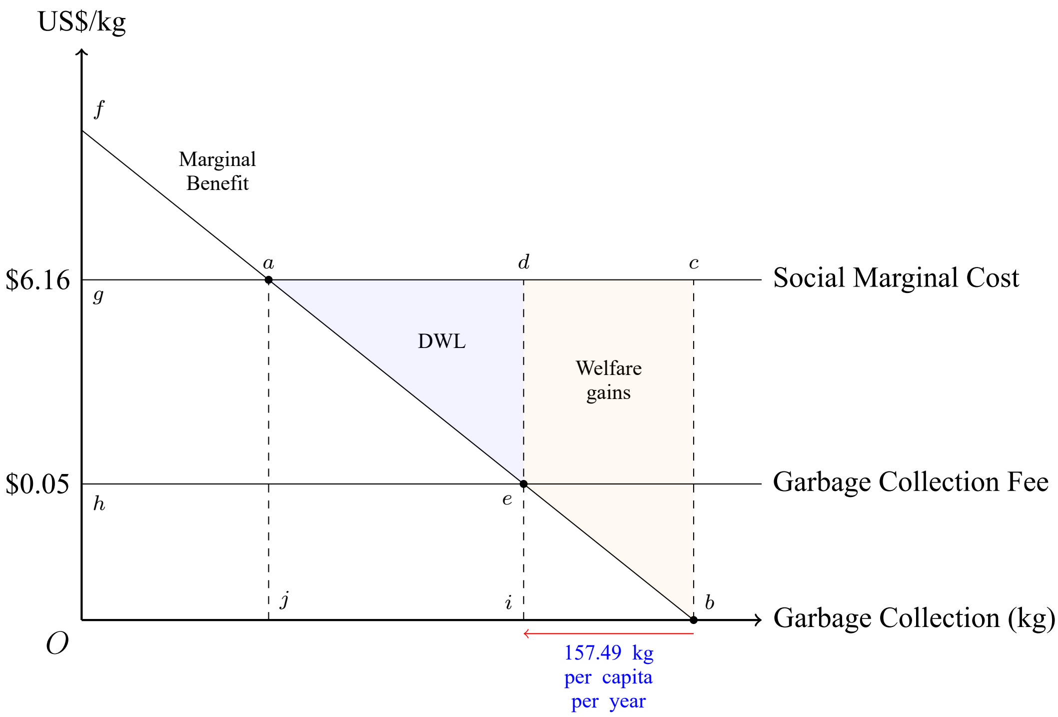


(e) Total



Notes: These graphs show the robustness of de-trended series for New Taipei City (solid) and synthetic New Taipei City (dashed). The demeaned synthetic control is applied to the de-trending waste series which is subtracted with controls' averages in each period. The two vertical lines denote May and November of 2010, when the main PBCF policy was implemented in 23 districts of New Taipei City.

Figure 10: Welfare Analysis



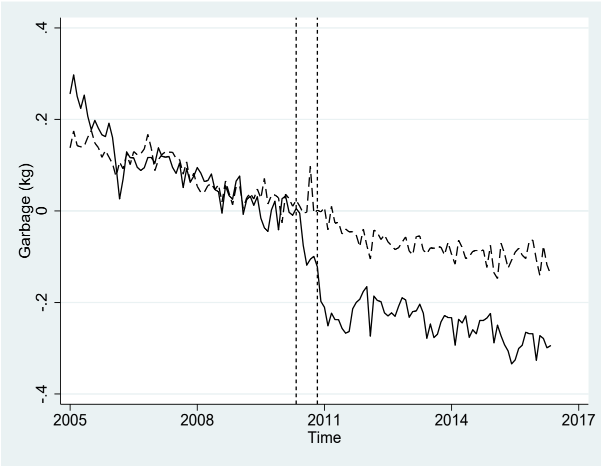
Online Appendix

A Seasonal Adjusted Waste Series

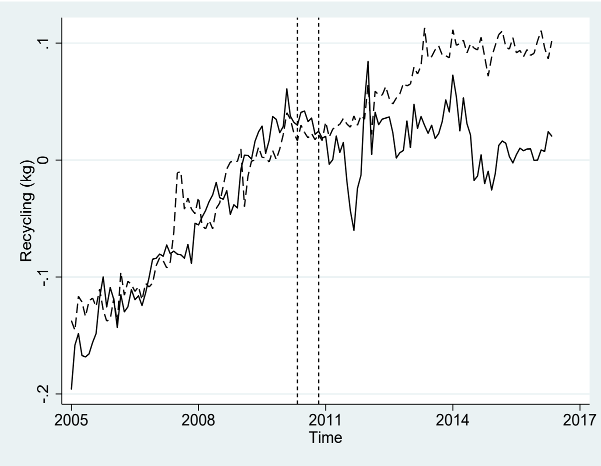
Monthly waste series contain monthly or seasonal effects. For example, traditional festivals, such as Chinese New Year or moon festival, may increase waste generation in specific months which lead to monthly volatility in waste series. To control for monthly effects, we regress waste series on monthly dummies to remove monthly effects before applying synthetic control. Figure A1 displays the synthetic control estimates when we use residualized waste outcomes that removes monthly effects. The new waste series appear to be less volatile, but the estimated gaps between New Taipei City and synthetic New Taipei City are similar with those in Figure 3.

Figure A1: Synthetic Control Using Seasonal Adjusted Waste Series

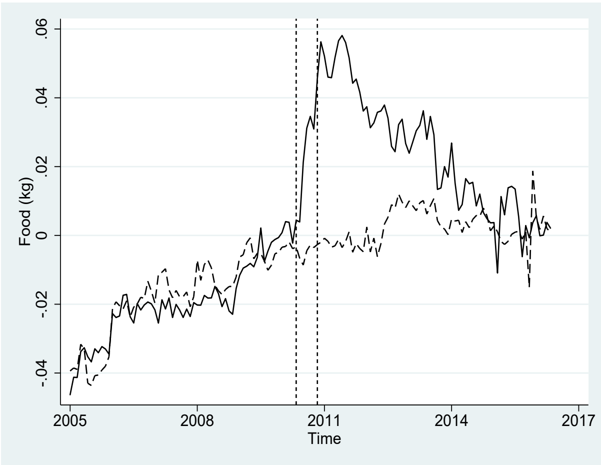
(a) Garbage



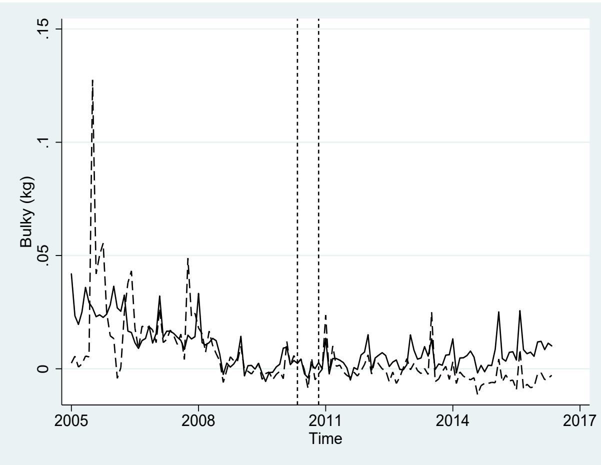
(b) Recycling



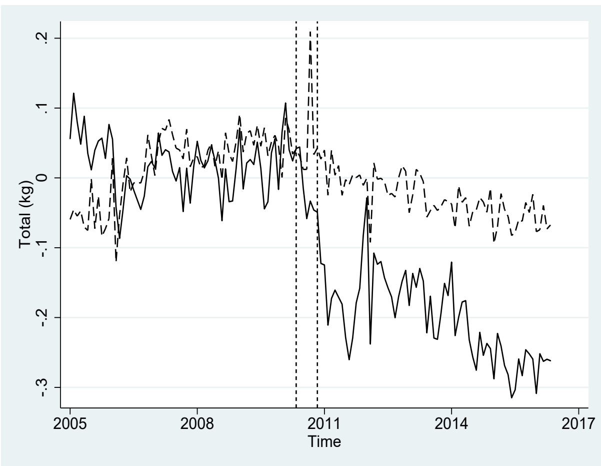
(c) Food



(d) Bulky



(e) Total



Notes: We eliminate the monthly effects by regressing waste outcomes on monthly dummies. We apply the synthetic control method to the residualized outcomes that partial out monthly effects. The solid line indicates the New Taipei City waste residual and dashed line indicates the synthetic New Taipei City. The two vertical lines denote May and November of 2010, when the main PBCF policy was implemented in 23 districts of New Taipei City.

B Additional Tables and Figures

Table B1: Difference-in-Differences Estimates

	(1) Garbage	(2) Recycling	(3) Food	(4) Bulky	(5) Total
D_{jt}	-0.210^{***}	-0.037^{***}	0.032^{***}	-0.002	-0.217^{***}
	(0.017)	(0.011)	(0.004)	(0.002)	(0.019)
City FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	2,466	2,466	2,466	2,466	2,466
R^2	0.786	0.804	0.729	0.265	0.634

Notes: This table estimates the effects of the PBCF on waste dumping per capita per day. We estimate equation 2 using data from all cities/counties except Taipei from 2005 to 2016. Standard errors are clustered at the city/county level. ***, ** and * indicate the significance levels of 1%, 5% and 10%, respectively.

Table B2: Synthetic Control Estimates With and Without Covariates

	(1) Garbage	(2) Recycling	(3) Food	(4) Bulky	(5) Total
With	-0.161	-0.052	0.022	0.007	-0.163
	(1/17)	(1/17)	(1/17)	(13/17)	(1/17)
Without	-0.181	-0.058	0.034	0.008	-0.188
	(1/17)	(1/17)	(2/17)	(15/17)	(1/17)

Notes: This table compares the synthetic control estimates using pre-treatment outcomes and covariates as predictors and those using only pre-treatment outcomes as predictors. The values in parentheses are the *p*-values from RMSPE-ratio tests.

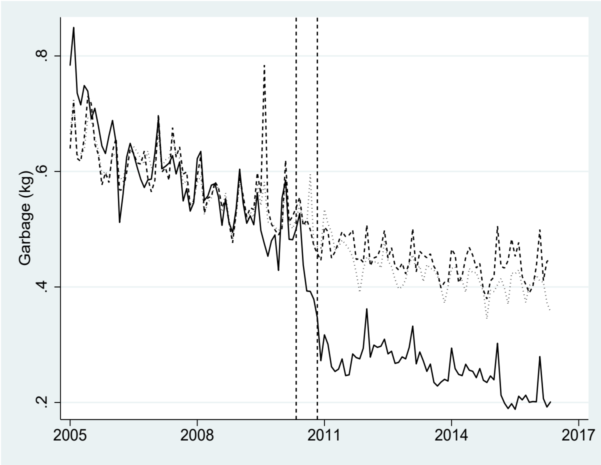
Table B3: Synthetic Control Estimates With Sorted Waste as Covariates

	(1) Baseline	(2) Recycling	(3) Recycling+Food
Garbage	-0.161	-0.164	-0.164
	(1/17)	(1/17)	(1/17)

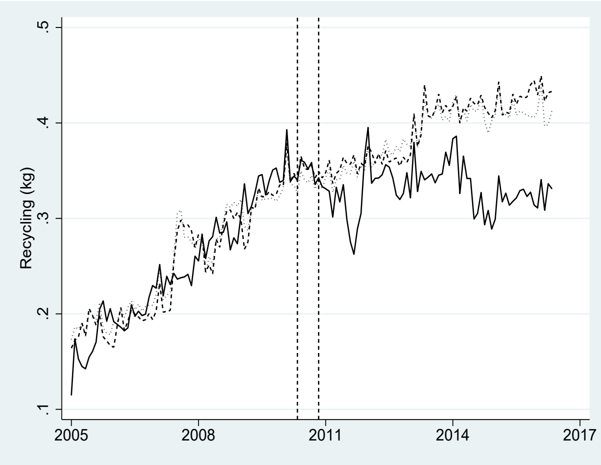
Notes: This table investigates the sensitivity of our synthetic control estimates to the inclusion of sorted wastes as predictors. The values in parentheses are the *p*-values from RMSPE-ratio tests.

Figure B1: Synthetic Control Without Covariates

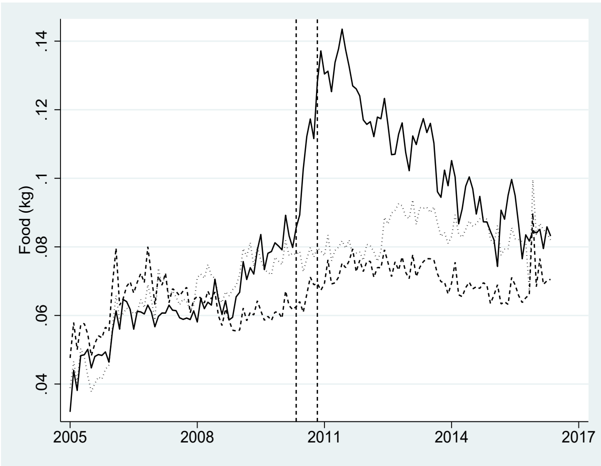
(a) Garbage



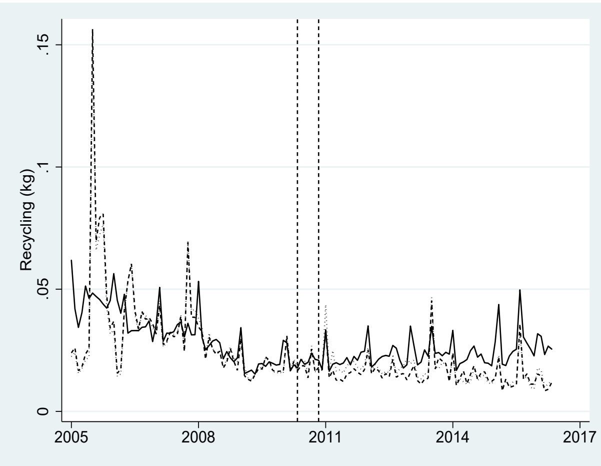
(b) Recycling



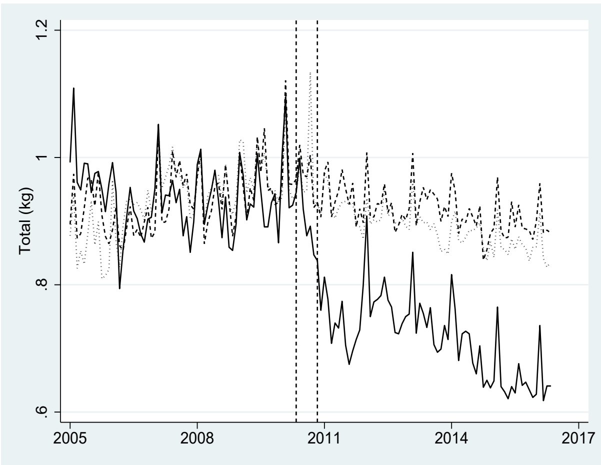
(c) Food



(d) Bulky



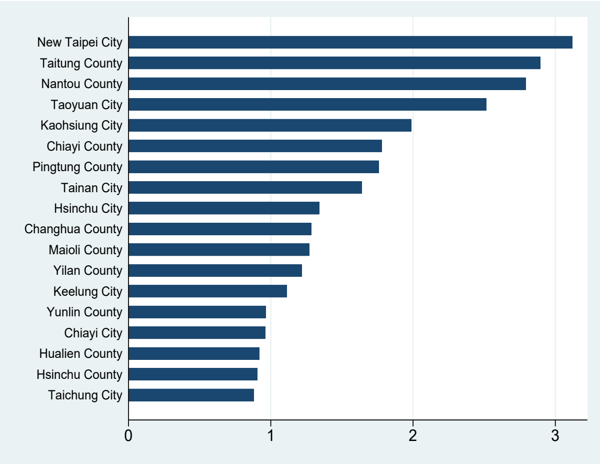
(e) Total



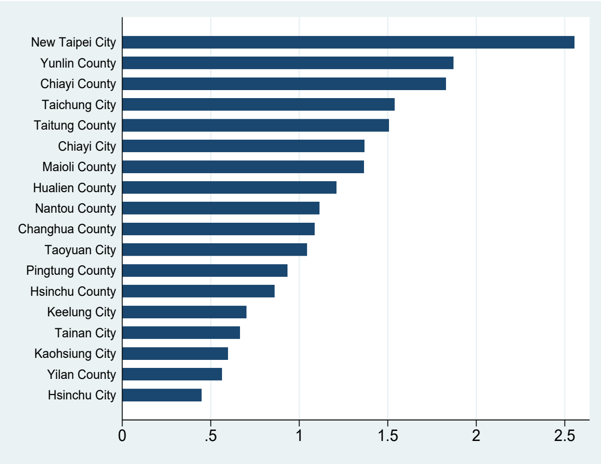
Notes: These graphs shows the robustness of synthetic control excluding covariates. Synthetic control is applied only with pre-treatment outcomes. The solid line indicate the New Taipei City waste series, the dotted line indicates the synthetic New Taipei City estimated using covariates and lagged outcomes as predictors, and the dashed line indicates the synthetic New Taipei City estimated using only lagged outcomes as predictors. The two vertical lines denote May and November of 2010, when the main PBCF policy was implemented in 23 districts of New Taipei City.

Figure B2: RMSPE Ratios Without Covariates

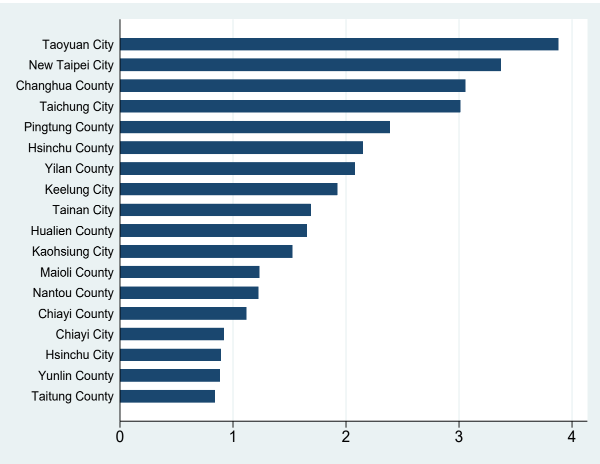
(a) Garbage



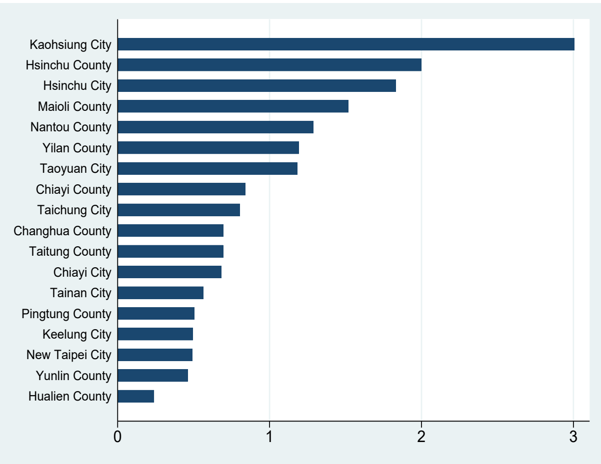
(b) Recycling



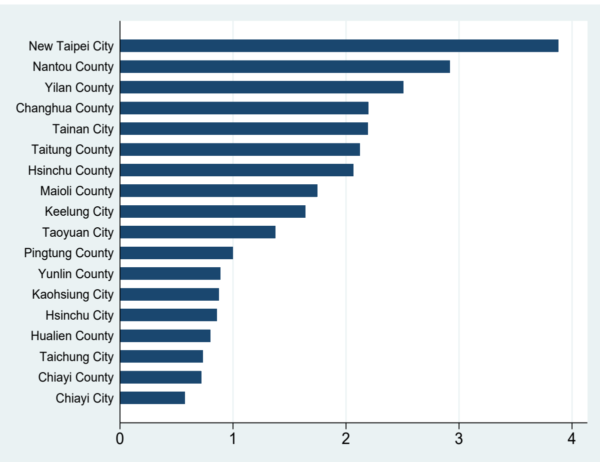
(c) Food



(d) Bulky



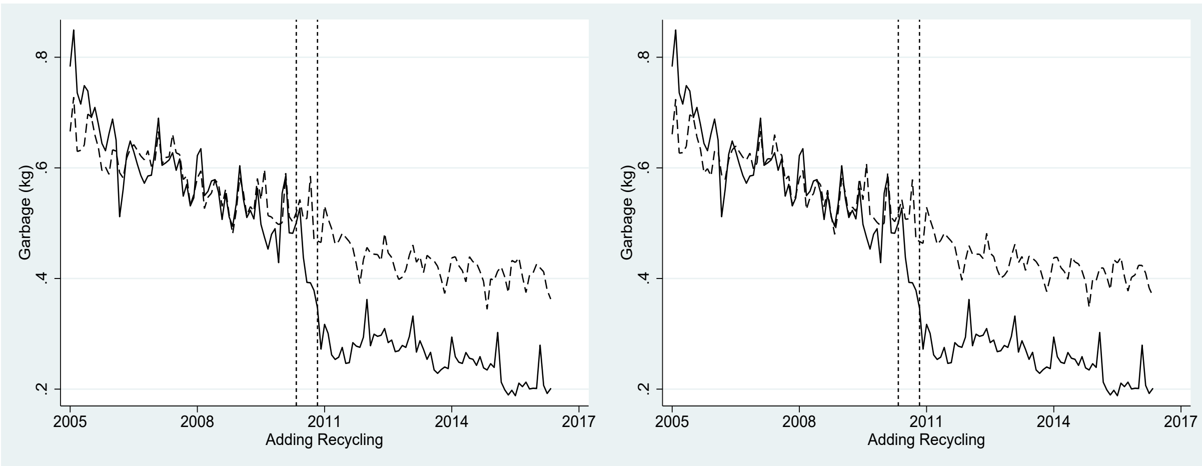
(e) Total



Notes: This figure displays the ratio of post-RMSPE and pre-RMSPE for New Taipei City and the 17 donors using the synthetic control estimates without covariates as predictors for optimal weights.

Figure B3: Synthetic Controls Including Sorted Waste as Predictors for Garbage

(a) Recycling (b) Recycling and Food Waste



Notes: These graphs shows the robustness of considering sorted waste as garbage's covariates. The left panel adds recycling as a covariate and the right panel adds both recycling and food waste as covariates. The solid line indicates the New Taipei City and dashed line indicates the synthetic New Taipei City. The two vertical lines denote May and November of 2010, when the main PBCF policy was implemented in 23 districts of New Taipei City.

隨袋徵收政策的影響—來自合成控制法的證據

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關鍵詞：隨袋徵收、合成控制法、垃圾迴避、垃圾替代

JEL 分類代號：D01, C21, Q53

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摘要

為了減少廢棄物，垃圾按量收費政策已在全世界廣泛的執行。本文旨在評估新北市的垃圾按量收費政策—隨袋徵收政策—對家庭廢棄物處置的效果。依據隨袋徵收政策，居民傾倒未分類垃圾時需要使用付費購買的認證垃圾袋，但傾倒已分類垃圾（包含廚餘以及可回收物）不須付費。我們運用合成控制方法控制不同縣市在垃圾處置上的時間趨勢，並以縣市層級的政府公開資料估計，發現隨袋徵收政策之實施降低未分類垃圾量約 27.2% 以及回收量約 20.8%。在短時間內，廚餘回收量幾乎翻倍，但其效果隨時間遞減。整體而言，該政策降低總垃圾量約 17.4%。這些結果支持垃圾單位計價不僅造成未分類廢棄物的垃圾迴避，同時也導致可回收物的垃圾迴避。最後，我們估計隨袋徵收政策每年為每家戶帶來 30,000 元的社會福利增益。